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Identifying the mode and impact of technological substitutions

Historical influences and evolutionary patterns

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By

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Abstract

Technological substitutions play a major role in the research and development efforts of most modern industries. If timed and provisioned well, successful technology substitutions can provide significant market advantages to firms that have anticipated demand correctly for emergent technologies. Conversely, failure to commit to new technologies at the right time can have catastrophic consequences, making determining the likely substitution mode of critical strategic importance. This issue is exacerbated for organisations with 20 to 30 year technology development cycles, such as in the aerospace sector, where it could take many years of resource commitment to observe and fully understand development potential of new technologies. With little available data, being able to identify at an early stage whether new technologies are appearing in response to a perceived stagnation in technical developments (potentially signalling a rapid change about to take place), or as a result of pioneering leaps of scientific foresight (potentially signalling the need for a longer development cycle), poses a significant challenge.

This research combines bibliometric, pattern recognition, and statistical approaches with data-driven simulations to develop technology classification and substitution models from historical datasets where literature evidence supports mode labelling. The resulting functional regression classification model demonstrates robust predictive capabilities for the technologies considered, supporting the literature-based substitution framework applied, and providing evidence suggesting substitution modes can be recognised through automated processing of patent data. Further, a system dynamics model enables the impact and causal influences of different substitution modes to be explored. Lastly, preliminary evidence suggests classification and forecasting can be achieved based on partial time series. This implies that future extensions to real-time applications may be possible for use in early stages of research and development. This capability would reduce uncertainty in decision-making, and consequently, time-to-market, enabling robust product/service strategies to be developed in response to continually evolving markets.

Dedication and acknowledgements

To say it has been a marathon trying to complete an engineering doctorate would be an understatement. Realistically, it has been a series of marathons from one day to the next. At times exhilarating, at times all-consuming and unattainable, it certainly feels like the doctorate has explored the boundaries of my sanity (...though as my family and friends will more than happily testify, this has been in doubt for a great many years!). It feels like these five years have gone fast for me, but this represents much more than just my effort. This work is dedicated to everyone who has helped in this undertaking.

Throughout all of this my partner Laura has been my best friend, confidant, and companion, and has never ceased to amaze me with her enduring love and support (even acting as a communication conduit for me to the outside world when I was locked-away in my 'EngD cave/bunker', and crucially, ensuring frequent supply of biscuits). She is a phenomenally hard-worker, and her dedication, inquisitiveness, and eagerness to learn are infectious. More than that, she is a great person to share life's adventures with, bringing the inspiration, humour, and music, to our home when it was needed most. I cannot thank her enough for her patience and encouragement during this time. No matter how erratic my working hours became, she was always in my thoughts. In the absence of children, our combined pride and joy is of course our amazing Labrador Belle, who is clearly the sanest of all of us at this time.

I also need to mention the rest of my family (mainly in therapy sessions); I have always felt lucky to have grown up in such a loving, warm, and in hindsight, incredibly animal-friendly home. I was never far from illuminating discussions on the subtleties of ancient Minoan cultures (or more commonly, *"What did the Romans ever do for us?"*), the greater works of Tolkien and Pink Floyd, geological processes that formed our favourite dog-walking haunts, or the latest veterinary procedures for large-animal endoscopies. Such wonderfully varied and free-thinking discussions made me realise how much I had to learn about the world. Similarly, it taught me to be open-minded, not to rein in my curiosity, and the value of asking questions (it also taught me that I understood technology far better than geopolitical history). For this, I have to thank my Mum, Dad, Paul, and additional canine friends, who gave me such an ideal environment to grow up in. I really could not have had a better, or more enjoyable, start to life then I did thanks to my family, so for that I am eternally grateful.

It goes without saying that this work could not have been undertaken without the support of the Systems Centre staff, teachers, my comrades-in-arms in our EngD cohort, and ultimately the EPSRC. However, my academic and industrial supervisors played a key role in exploring the research questions, concepts, and rigour of the study, whilst persisting with complex topics. As such, I am very thankful to Professors

Chris McMahon, Mark Lowenberg, and Dr. Sanjiv Sharma for their continued time and efforts. I'm also particularly indebted to my good friends and colleagues at Airbus, Ranjit Ravindranath and Mark Hall, who have frequently acted as sources of motivation (knowing when I needed that little extra push!), and honest sounding boards for my more crazy, sleep-deprived, ideas. Equally, to Chris Lynas, Llifon Williams, and Dave White, who have put up with my academic musings and trouble-making throughout, and who have stuck with this despite any misgivings they may have had. Thank you for giving me the opportunity and the time to work on this; the doctorate simply could not have been completed without your support!

There have been many things I've missed during this period that I really wanted to give more attention to – my long-suffering partner Laura knows this only too well! So this dedication is also a way of saying sorry to all those family and friends I have not had chance to keep up with, or give the necessary time to, over the last few years. Perhaps most of all, Laura, my family, friends, and loyal canine companions, have always reminded me of what the world is about, what matters, and why I got into engineering in the first place; *to make a difference*. This dissertation is certainly not the end of the story, but hopefully it goes a little way towards that, and towards repaying my debt to the people who have enabled me to become the slightly more deranged and unhinged engineer I am today.

"Do or do not. There is no try"

- Yoda, The Empire Strikes Back *(p.s. ...and thank you George Lucas for everything Star Wars related)*

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Abbreviations

ABM Agent-Based Modelling.

ARPA U.S. Advanced Research Projects Agency.

ATS Air Transportation System.

CFL Compact Fluorescent Lamp.

CLD Causal Loop Diagram.

CPC Cooperative Patent Classification.

CRT Cathode Ray Tubes.

DfT Department for Transport.

DII Derwent Innovation Index.

DNA Dynamic Network Analysis.

DOE U.S. Department of Energy.

DTW Dynamic Time Warping.

FCC U.S. Federal Communication Commission.

GE General Electric.

HPM Hierarchical Process Model.

ICCT International Council on Clean Transportation.

IP Internet Protocol.

IPC International Patent Classification.

LCD Liquid-crystal display.

LFT Linear Fluorescent Tube.

LTS Large Technological System.

NCP Network Control Protocol.

OTEC Ocean Thermal Energy Conversion.

PAS Purposeful Activity System.

PSM Problem Structuring Methods.

PV Solar photovoltaic.

SD System Dynamics.

SSM Soft Systems Methodologies.

TCP Transmission Control Program.

TFT-LCD Thin-film-transistor Liquid-crystal display.

TLC Technology Life Cycle.

URL Uniform Resource Locators.

WIPO World Intellectual Property Organization.

Chapter 1

Introduction

The introduction of new technologies into heavily regulated industries such as aerospace is often a very complex, time-consuming, and expensive challenge that requires significant research and development efforts to ensure a successful technology substitution. This challenge is exacerbated when new technologies represent a fundamental shift away from well-established principles, as the risk and uncertainties involved increase significantly. This is the case in the anticipated transition from conventional turbomachinery-based aircraft to all new electric configurations, and equally for the adoption of technologies enabling mass manufacturing and customisation in aerospace production lines. Simultaneously, the opportunities associated with these disruptive innovations may be sufficient to warrant decision-makers adopting new technological approaches. In some cases, new technological frameworks arise whilst existing technologies are still undergoing further developments, and have not yet reached the peak of their performance. This further complicates choices for decision-makers, as devoting significant resources to a new technological approach that may or may not out-perform existing ones presents great commercial risk. The potential for high gains or equally high losses arising from the technology adoption choices made by a company reflects the importance of these substitution events for long-term planning, meaning they are often considered of critical strategic importance. It is therefore beneficial to be able to identify early whether an emerging technology is likely to have scope for development beyond that of the current dominant technology, and commercially when the tipping point might occur where the new candidate would become the industry 'mainstream' technology option.

The commercial growth opportunities within Large Technological Systems (LTS), such as the aerospace sector, are significant: Airbus' Global Market Forecast identifies the need for almost 20,000 new single aisle aircraft alone by 2030 [Airbus S.A.S, 2013]. This is partly to replace existing aircraft but also to support increasing traffic in both established and emerging markets. Fleet growth is also expected in the twin-aisle and large aircraft markets, bringing the expected value of market growth to more than $4 trillion [Airbus S.A.S, 2013].

The size and complexity of this market means that success in securing new aircraft sales will depend upon being able to deliver a product meeting the needs of a wide range of Air Transportation System

(ATS) stakeholders, each with different strategic goals. Given the significant growth expected, there is much to gain in the aviation industry, but equally, much to lose for incumbent firms. As a result, within technology and product development decision-making, significant emphasis is often now put on risk management to minimise exposure to technology and market volatility. In the case of technological substitutions, the benefits and risks of the new technology may not be immediately apparent without an existing comparable example to gauge it against. Typically, risk is quantified as the financial investment, time, and effort required for the development of the new technology that is lost if the project is not successful, whilst the benefits will most likely be defined via existing 'legacy' performance metrics (at least initially). In aviation, weight and fuel burn have conventionally been the performance metrics driving technological improvement, but recently alternative metrics have become important, which relate more closely to customer service (such as the aircraft's impact on airport capacity constraints). Whilst the metrics that characterise the benefits of an emerging technology may evolve over time, the performance expectations that drive adoption of new technologies are often rooted in existing scientific principles. Consequently, studies of historical adoption patterns and market responses for emerging technologies driven by scientific, rather than commercial, expectations may provide better insights into how the performance of future innovations will evolve.

Disruptive innovations also present greater benefits and risks compared to incremental developments, arising from the gamble of being 'first-mover' in a new field. Although costs and learning curves associated with prototyping, development, and industrialisation for disruptive technologies are often steep, the rewards for being first to capture the market can equally be of great significance. Conversely, adopting a low cost, low technical risk, incremental development strategy can sometimes be higher risk than adopting a new technological paradigm if the incremental technologies developed are easily replicated, or leap-frogged, by competitors. In the worst case, companies may commit extensive resources to technologies and strategies that may be obsolete by the time they come to market. This emphasises a frequent challenge for businesses; the future viability of a new technology, product, or service is often uncertain, and assessing its viability during developmental stages is difficult. Consequently, forecasting techniques are often used by businesses to project market outcomes and determine strategies, by providing a guide to future opportunities, risks, challenges, and areas of uncertainty.

Forecasts are used in many sectors to provide guidance on the implications of potential changes: from predictions of changing weather patterns, to projections of a nation's financial outlook, and warnings of traffic congestion in satellite navigation systems. Computational power has grown dramatically since early numerical methods, so modern forecasts are often based on computer-generated simulations of the world (alongside other non-computational approaches such as industry surveys and expert-elicitation). Computer-generated forecasts are increasingly used to simulate possible outcomes of disruptive changes which cannot be easily or safely reproduced by other methods (such as modelling natural disasters and large-scale social disruptions). Ultimately, the increasingly complex nature of the ATS, and other LTS (which include technical, economic, cultural, and organisational technology adoption influences), means data-driven models may be helpful to enhance understanding of technology's impact on market evolution.

More specifically, the ability to recognise a new technology's mode of adoption early in its development, based on historical patterns, would provide a clearer view of the long-term commercial potential of that technology. In this regard, recent advances in pattern recognition and behavioural modelling techniques may assist the comprehension of complex socio-technical influences behind technology substitutions in LTS. This study attempts to bridge the gap between technology performance expectations, development patterns, and market uptake, to improve the robustness (and therefore likelihood of success) of technology development decisions during conceptual design stages.

The perils of a rapidly changing technology roadmap are illustrated by a survey conducted by a large UK manufacturing organisation, examining the impact of *Undesirable Effects in Design to Manufacture*. Although the survey was conducted 10 years ago, issues similar to those highlighted in it remain. This study revealed that consistently more time was spent re-planning work than actually progressing it [Lear, 2007], and that much of this re-planning stemmed from the oscillation between conflicting business directions. Over 300 Undesirable Effects (UDEs) in Design to Manufacture were identified from 691 reported observations, and through a cause and effect analysis, 22 primary UDEs responsible for this situation were highlighted. These results were ratified by representatives from all parts of the UK business. For product development programs the most significant standalone undesirable event in design is perceived to cost upwards of £3 million to rectify. The survey also identified that delays associated with immature tools and processes can account for over a year's worth of additional effort, whilst time wasted gathering and reformatting data, and reworking components, can cause delays of more than 5 and 6 months respectively. Instances of component re-work in particular were perceived to account for over £2 million of additional costs during this 6 month period. Finally, the survey identified that the impact of not working to originally agreed plans accounted for an additional 50% of required effort.

Perception of cost can be as important as actual costs for decision-making, as in many cases forecasted costs are used, rather than already known costs. The results of this analysis suggested that 5% of the UDEs observed in 2007 cost more than £1,000,000, 6% cost more than £100,000, 12% cost more than £10,000, 16% cost more than £1,000, and 6% cost more than £100. Combining these minimum category values with the expected frequency of UDE occurrences (shown in Fig. 1.1), this equates to over £250 million per year perceived as spent on UDEs in this UK manufacturing operation.

Previous historic studies have estimated that 65% of aircraft lifecycle costs (LCC) are effectively 'locked-in' during conceptual design stages, with 85% of LCC 'locked-in' by the end of the preliminary design stage [Roskam, 2005]. This potentially suggests that 65% of annual UDE costs (i.e. over £160 million) may be connected to decisions taken during the conceptual design phase. This is particularly significant given that many aircraft have lifespans of 30 to 40 years (or more) and undergo numerous modifications during their operational life [Carter, 2001]. Consequently, this highlights the need to develop stable views on technology development trajectories at the earliest stage of design, to minimise as much as possible the recurring costs that arise later from re-configuration of products, designs, tools, and processes.

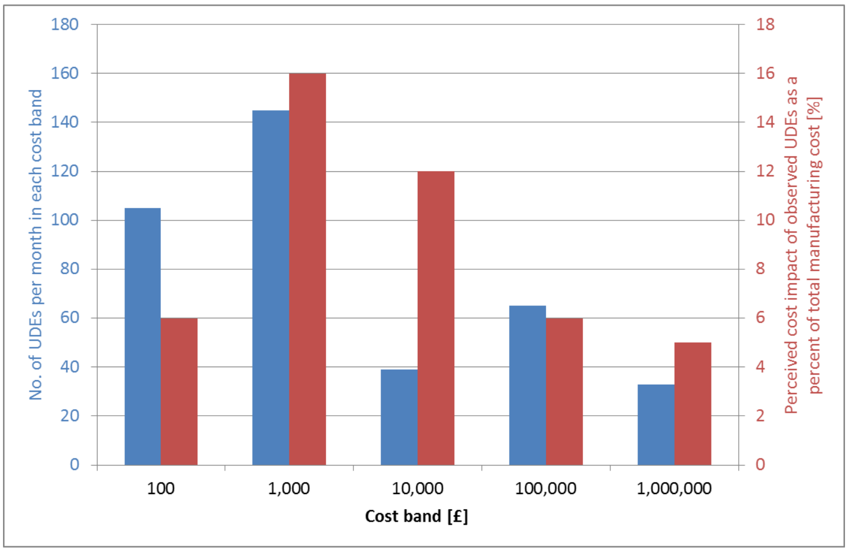


Figure 1.1: Frequency and cost of UDEs in manufacturing operations
(based on survey results in Lear [2007])

1.1 Research purpose

The purpose of this study is stated as the development of a modelling framework to identify substitution modes and test the sensitivity of adoption behaviours to these modes for emerging technologies in Large Technological Systems, such as the ATS. The models developed here are intended to form part of a product and technology lifecycle management toolset, enabling dissimilar technology options (potentially at different stages of development) to be evaluated against performance expectations and anticipated market responses. Hypothetical product and technology 'roadmaps' could then be tested against market responses, to inform systematic targeting of funding and bring technology performance to required levels at or ahead of the expected time, thereby guiding technology substitution.

1.2 Research objectives

To meet this purpose, the following research objectives are defined, whilst study hypotheses, research questions, boundaries, desired outcomes, and research strategy are explored further in chapter 3.

1. Identification of technology substitution patterns and characteristics in LTS in relation to scientific & technological development efforts and other socio-technical influences.
2. Identification of historical technology substitution case studies to determine the impact of different patterns of scientific & technological development efforts on global technology adoption trends.
3. Exploration of whether and how features extracted from historical datasets may be used to classify technologies
4. Investigation of whether it is possible to construct and validate a dynamic technology adoption modelling framework for use in conceptual design, based on identified substitution patterns and case studies.

Consequently, the end focus of this study is to investigate whether a modelling framework can use data-driven technological development patterns to reproduce observed substitution behaviours for a range of historical case studies and infer future trends.

1.3 Research outcomes

The main study hypothesis is that:

1. technology substitutions may follow one of several potential substitution modes;
2. the mode that a substitution falls into is dependent upon either performance expectations or relative scientific and technological development efforts;
3. it is possible to recognise these modes from the emergence of patterns in technology datasets.

Accordingly, this study adapts technology forecasting techniques from existing literature, coupled with statistical and functional data analysis of historical patent data, to explore:

1. the conditions required for technological substitutions to arise.
2. the formulation of a functional linear regression model that indicates the likely mode of adoption from key technology development indicators.
3. a system dynamics simulation framework for assessing the impact of technological substitutions.

Combined, these elements provide a means to predict market receptivity and support technology strategy and innovation management. This enables quantitative (i.e. data-driven) measures of scientific development to be considered alongside more qualitative socio-technical influences, as part of wider technology development and market adoption processes.

Beyond this, in terms of the direct return on investment (ROI) of this study, the case for modelling and simulation is often difficult to quantify (as the alternative cases of not undertaking modelling and simulation are not usually measured), although existing literature provides some insight. Pharmaceutical and material science companies (which face similar development programme overheads and timescales to aviation due to an equally stringent level of safety regulations), are quoted as receiving between $3 and $9 ROI for every $1 invested in modelling and simulation [Carter, 2001, Swenson et al., 2004]. It is therefore believed that the models developed in this study, if not the end product in themselves, will provide a benefit to decision-making that will enable similar improved efficiencies.

In this instance, the capability to identify and test the sensitivity of the mode of substitution for a given technology will reduce uncertainty in decision-making processes by providing a clearer view of the risk of obsolescence of technologies and designs at the earliest conceptual stages. This would enable a business to identify transition points where new products or upgrades should be phased in, based on the translation of expected performance characteristics into projected market share, with increased confidence. A more focused technology roadmap can then be implemented that offers a reduced time-to-market, whilst allowing product and service strategies to be developed that are more robust to shifting technological, market, and environmental conditions. This approach also enables a move away from purely product-based development strategies, as the ability to compare dissimilar technologies allows promising general-purpose technologies to be identified earlier, which are 'product-agnostic' (e.g. technologies that are likely to be of value irrespective of which product they are applied to).

1.4 Research structure

To begin with this study explores the relationships between technological substitutions, scientific and technological development, large technological systems, and technology forecasting techniques in chapter 2. A more detailed examination of the problem structure, research questions, and research strategy is subsequently discussed in chapter 3, followed by a review of possible methodological approaches and modelling challenges in chapter 4. Derivation of the technology classification model using statistical ranking and functional data analysis is then provided in detail in section 5. This is followed by the construction of a technology substitution model based on system dynamics in chapter 6, as a proof-of-concept of potential technology forecasting applications. Finally, conclusions and discussions on the implications of the ideas explored relating to technology substitution in the earlier chapters are summarised in chapter 7. To provide a clearer overview of the main themes and concepts applied in formulating the framework described in this study, an outline of the chapter structure is provided in Fig. 1.2. First though, the characteristics and modelling of substitutions in large technological systems are considered in more detail in the next chapter.

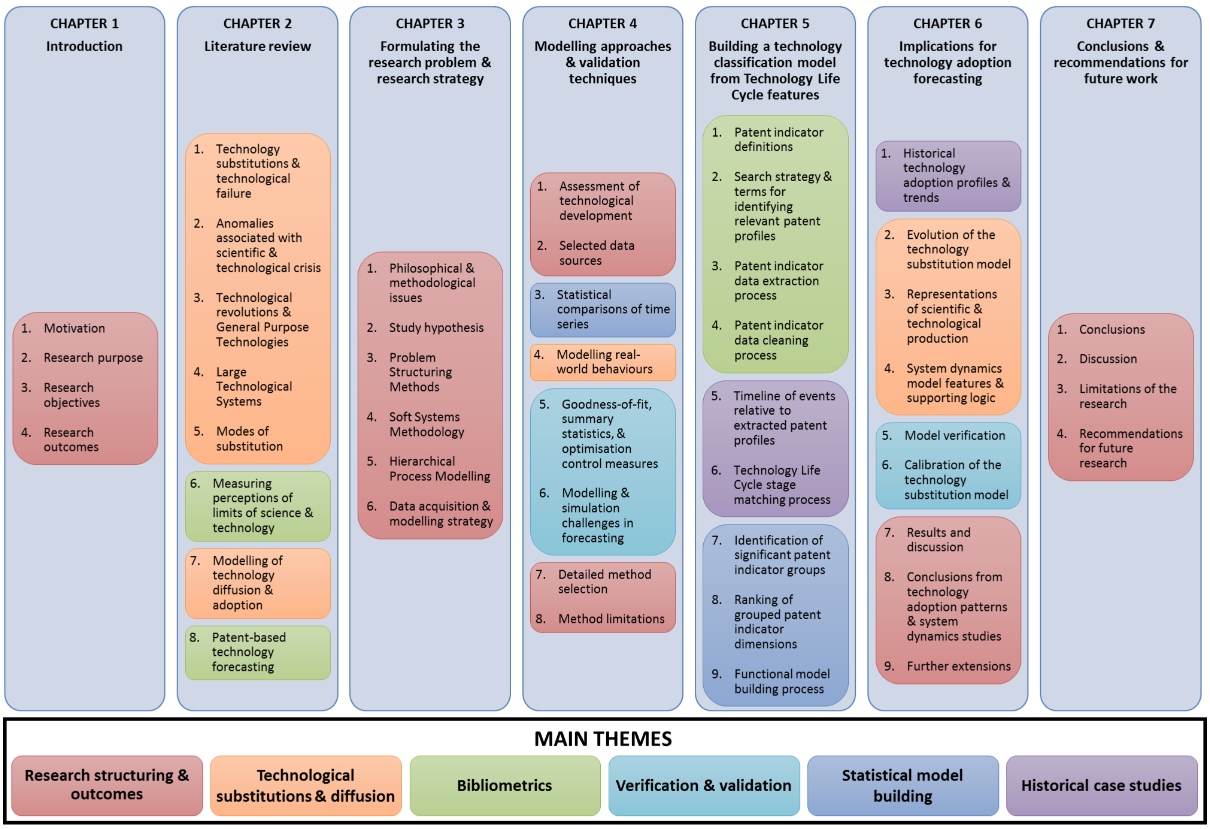


Figure 1.2: Chapter structure and main themes

Chapter 2

Literature review

As outlined in the previous chapter, technological substitution often plays an important role in the fortunes of businesses. Numerous studies have examined the many complex factors that influence technology development and adoption trends. This chapter provides an overview of the relationships between technological performance, perceived limits of science and technology, observed substitution patterns and behaviours, general purpose technologies, large technological systems, and technology forecasting techniques, to explain the analysis that follows.

2.1 Technology substitutions and technological failure

Technology substitutions occur when an incumbent technology is replaced by a radical innovation resulting in a new socio-technical regime [Geels and Schot, 2007]. Consequently, correctly predicting which emerging technologies are likely to be most influential can ensure that a company is best positioned to gain an advantage over its competitors when the new technology comes to fruition. Conversely, failure to anticipate the arrival of large technological shifts can leave businesses severely diminished. This is often illustrated by the dramatic impact on Kodak's business following the introduction of digital photography that rendered many of the company's existing film products obsolete, following an early lead in the digital field that was not fully capitalised upon [Lucas and Goh, 2009]. Equally, investing heavily in a nascent technology too soon can have grave consequences, as Bertlesmann found from investing in Napster [Hall and Rosson, 2006]. As such, forecasting techniques are commonly used to determine strategies in large organisations by providing an initial guide to future opportunities, risks, challenges, and areas of uncertainty [Daim et al., 2006].

Considerable work has already been undertaken on modelling technology diffusion in these substitutions. Technology diffusion examines the spread of new ideas and technology over time through social systems based on the communication of the innovation between individuals in the population [Rogers, 2010]. In this regard, technology diffusion theories and models attempt to explain the causes and transfer mechanisms supporting the spread of technology, as well as the rate at which this takes place. In the context of technological substitutions, technology diffusion therefore relates to the growth in adoption of an emerging technology amongst an existing population. Key elements considered in technology diffusion studies relate to the influences of inventions, adopters, communication channels, time effects, and social systems [Rogers, 2010]. Research has included, amongst other areas of study (see Peres et al. [2010]), the influence of successive technology generations, and the impact of delays on the perception of new technologies, as illustrated in Fig. 2.1 and Fig. 2.2 respectively. Forecasting techniques are discussed further in section 2.7, but are introduced here to explore the characteristics of technology substitutions that have shaped existing modelling efforts.

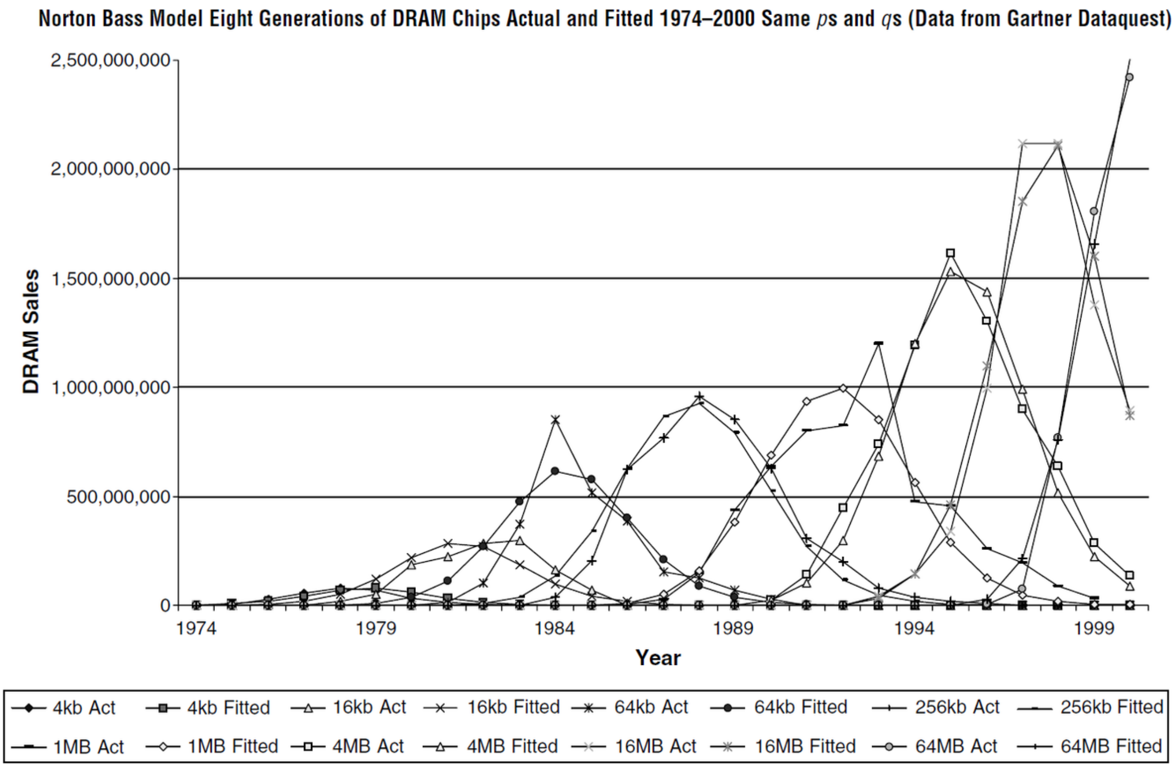


Figure 2.1: Successive generations of technology substitutions [Bass, 2004]

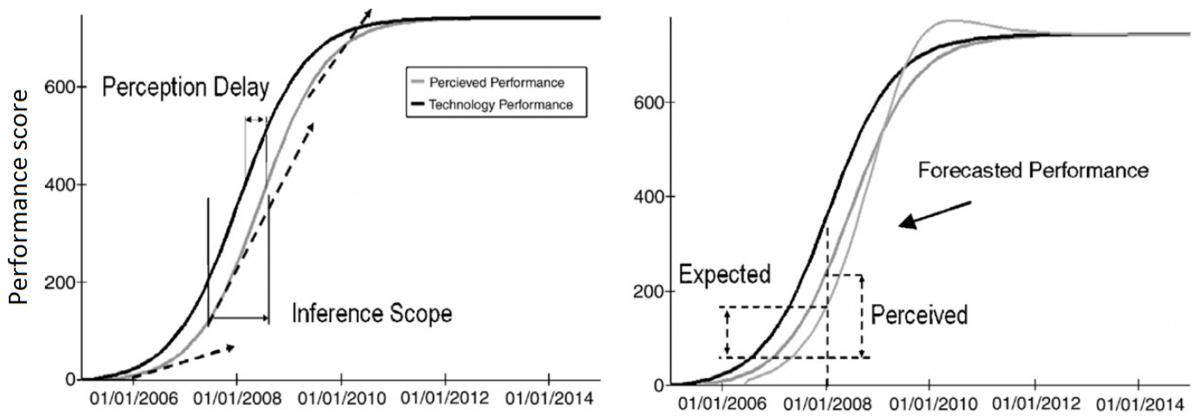


Figure 2.2: Technology S-curves and the impact of time delays on the perception of new technologies [Dattée and Weil, 2007]

The introduction of new technologies is often described as following two distinct, but related, S-curves [Adner and Kapoor, 2015]. The first of these is an S-curve that describes technological development in terms of the improving performance of the technology in question over time. The second, lagging slightly behind in time, then relates to the diffusion of this technology through a population as noted previously. The basic features of these two S-curves are shown in Fig. 2.3, whilst the relationship between these models is illustrated more clearly by the overlap visible in Fig. 2.4.

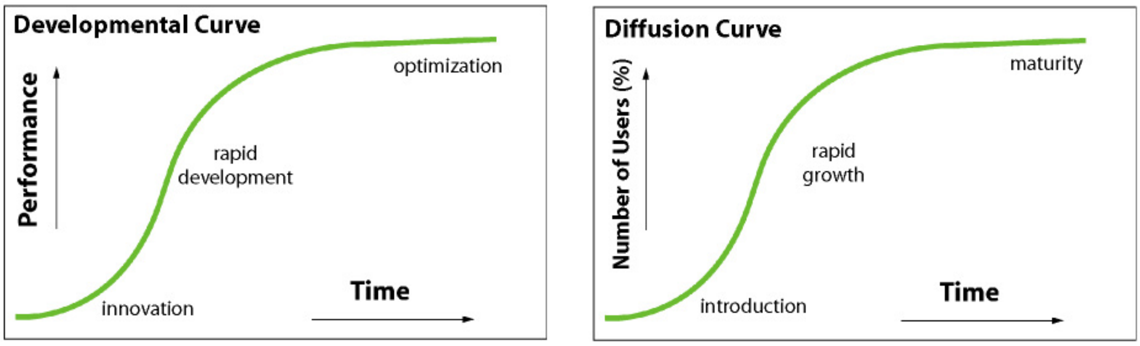


Figure 2.3: Technology development and diffusion S-curves [White, 2008]

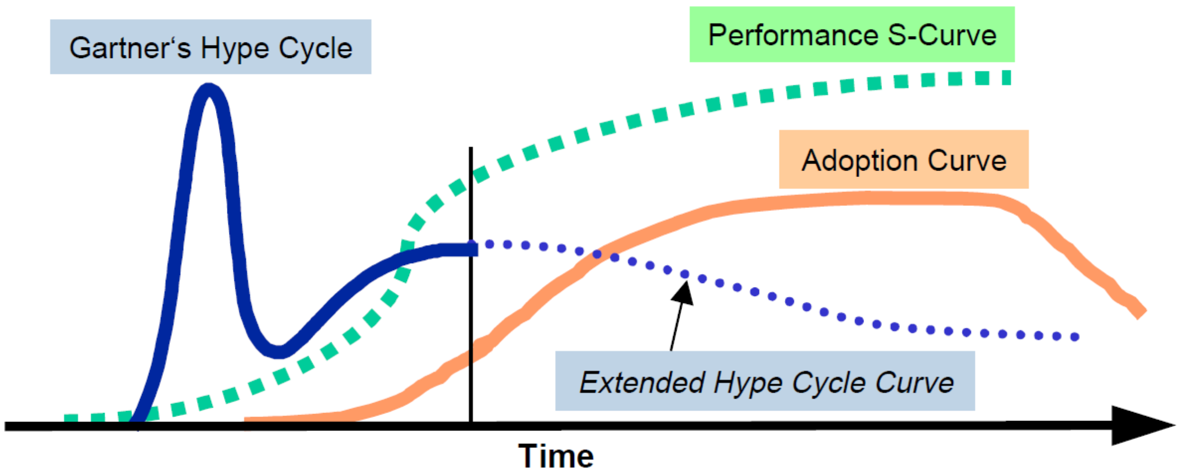


Figure 2.4: Relationships between technology development, diffusion, and hype cycle models [Linden and Fenn, 2003]

Technology diffusion S-curves assume uptake is initially slow in the earliest stages, until performance and functional benefits of the new technology (described by the technology development S-curve) are seen to be greater than those of existing technologies, at which point uptake significantly accelerates [Foster, 1986, Utterback, 1994]. Considering first the S-curve model of technological improvement, this assumes that all technologies eventually arrive, driven by research and development efforts, at an ultimate limiting condition based on physical constraints, where performance improvements stagnate once again. Foster describes the transition from wind-powered to steam ships in this context, where the speed of wind-powered vessels was inherently limited by the physics of wind and water [Foster, 1986, Christensen, 2009]. Accordingly, the Fisher-Pry model of technology substitution uses a single growth curve derived from biological systems to describe technological change [Fisher and Pry, 1971, Jeong et al., 2016]. However, periods of performance stagnation can also occur when challenging technical obstacles appear, or when market uptake slows (potentially due to market saturation, regulatory changes, or competition from new technologies), reducing investment in research and development [Myers and Marquis, 1969, Poolton and Barclay, 1998]. This results in substitutions to the next generation of technologies occurring either before or after arriving at a perceived performance limit, which may or may not be an actual, or ultimate, performance limit (see Fig. 2.5) [Adner and Kapoor, 2015, Hughes, 1983].

These observed performance plateaus create the notion of continual technological (or functional) failure, at the point where a replacement technology is sought for a currently stalled technological paradigm [Sood and Tellis, 2005]. However, the technological 'failures' that lead to this reactive type of substitution vary greatly, and cannot just assume a single simple definition. On this topic, previous work has examined what is meant by 'technological failure', and categorised these occurrences into three main definitions [Gooday, 1998]:

1. **'Failure' as a social taxonomy of marginalised technologies:** 'Failure' is not an essential characteristic of the technology itself. Instead 'failure' depends on a diverse range of usage factors that may not be replicated in other cultures, and is chronologically bounded so that any technology can be classed as a success or failure at any given time according to social responses to it. This implies that 'failure' is unexceptional in technology, and that all 'successful' technologies 'fail' at some point [Gooday, 1998]
2. **'Failure' as a mundane feature of technological usage and development:** Persistent 'failure' of technology is an unavoidable consequence of ever more demanding expectations that humans impose upon their all-too-limited constructions. What 'fails' is human expectations of hardware performance and distribution; a 'failure' of socio-technical relations [Pye, 1978, Gooday, 1998]
3. **'Failure' as a perspectival and often contested attribution:** Many recent sociological studies of technology employ two simplifying assumptions: firstly that there is a decisive closure point in history where a technology is judged a 'success' or 'failure', and secondly that at this point, all parties reach a decision that is consensual, despite being based upon differing perceptions of the technology's social role. Both of these assumptions can be challenged by strong counter-arguments [Gooday, 1998]

Beyond continually increasing human expectations of technology the work of Gooday therefore incorporates notions of non-linear development in the history of technologies (i.e. the stop-start nature of progress), the potential effects of social marginalisation, as well as demographic and cultural influences that can lead to a divergence of opinions of whether a technology has 'succeeded' or 'failed'. More recently, the work of Edgerton has delved further into these concepts by introducing the idea of *Creole* technologies that can appear, disappear, and subsequently reappear throughout the course of history, whilst also highlighting the lag between technology development and widespread use [Edgerton, 2011]. In this regard, segmentation of technology evolution into clearly defined sequential stages is not necessarily a straightforward task (as noted in section 4.7.1). Additionally, Edgerton contests the role of 'bleeding-edge' technologies, noting that conventional technologies have a remarkably long shelf-life, sustained impact, and are capable of resurgence [Edgerton, 2011].

The work of Gooday builds on preceding case study analysis compiled by Hans-Joachim Braun [Braun, 1992]. In this work, Braun reviews a diverse range of technologies labelled as 'failed innovations'. Table 2.1, derived from Gooday's review, summarises some of the socially marginalised technologies that were considered in this work, along with commentary on the reasons for being branded as a failure.

Table 2.1: Examples of socially marginalised technologies
[Gooday, 1998, Braun, 1992, Clawson, 1980]

Examples of marginalised technologies	Reason for being branded as a failure
Aero-diesel, air-cooled, copper-cooled, and coal-dust engines (1890s to 1940s)	Weight (aero-diesel), noise (air-cooled), maintenance costs (copper-cooled + coal dust), and explosion risks (coal-dust), without sufficient time and resources committed to rectify these issues in comparison to rival internal combustion engine developers
Electromagnetic focusing techniques in early electron microscopes (1940s & 50s)	Electrostatic focusing techniques were more in line with RCA and General Electric corporate strategies in the 1940s and 1950s
Ford's submarine chasing eagle-boats (World War 1)	Lack of labour skills resulted in unreliable production and manufacturing
Gas absorption refrigerator (1920s & 30s)	Eclipsed by the electric icebox (i.e. vapour compression refrigerators), due to lack of capital for product development and marketing
Pneumatic dynamite gun (1880s to 1900s)	Blocked by institutional resistance by factions in the American Civil war
Day-Cock two-stroke engine (1890s)	Failed due to bankruptcy of Joseph Day
Gemini paraglider (1950s and 60s)	Usurped by the more glamorous and demanding Apollo programme during the 1960s
Unsuccessful attempt to launch a gas turbine car engine (1960s and 70s)	Would have required hugely expensive re-tooling of Chrysler's mass-production infrastructure, which was not justified by very poor fuel economy
Electric plough (prior to World War I)	Too uncomfortably radical a transformation of agricultural practice for farmers in Wilhelmine, Germany. Superseded after World War I by tractors
All-plastic bicycle (1980s)	Considerable lack of enthusiasm in 1980s Sweden (too unlike a conventional bicycle to meet tastes and requirements) - question raised over whether this would have 'succeeded' a decade earlier during the 1970s oil crisis
Record-playback machine tools (1950s)	Record playback worked equally well for small shops and relied on the machinists' skill, while numerical control favoured large firms and promised to replace skilled machinists with computer synthesised processes
Transatlantic telegraph cable project (1850s and 1860s)	Cable laid between Ireland and Canada in 1858. Queen Victoria subsequently uses it to communicate across the Atlantic, resulting in it being hailed as a huge success. 2 months later the cable was no longer responsive to transmission equipment on either side of the Atlantic. Cable was then branded a 'failure', and telegraph company's electrician Wildman Whitehouse used as sole bearer of responsibility for the 'failure' (i.e. scape-goat). 1864-1866: new cable funded and laid, using lessons learned from problems with first cable, resulting in being hailed as heroic 'success' again

In his critique of Braun's work, Gooday's emphasis on marginalisation arising from both technical characteristics and social dynamics becomes more apparent. Consequently, the reasons for being branded as a failure presented by Gooday for the same case studies (shown in Table 2.1) tend to highlight the social dimensions of failure as a counter to the more technical focus presented by Braun. Asbestos is perhaps a classic example of this: whilst in many ways asbestos' broad-ranging technical and commercial performance characteristics have not been matched by later substitute materials, societal health concerns prompted the marginalisation and eventual banning of this technology in many countries (although still used even today in some nations). These examples demonstrate therefore the importance of considering technological substitutions from both a social and technical perspective to obtain a realistic understanding of their origin.

As Gooday states that the second form of technological failure is an unavoidable consequence of ever increasing human expectations, making it the most frequently observed type as part of the general technological development process, few examples are provided in his discussion. However, Gooday cites the evolution of multiplicity of paperclips as one example; many metallic designs were considered at the start of the twentieth century which were subsequently refined through successes and failures to the applications now associated with each design [Gooday, 1998, Schroeder and Petroski, 1994].

The last category of technological failure relates to the consensus that a failure has actually taken place. Here Braun notes that marketing performance, efficiency of development, favourable management characteristics, effectiveness of communications, and understanding of user needs were advocated as universal criteria for judging the success and failure of products from studies conducted in the 1970s and 1980s [Braun, 1992]. Braun counters this by noting the success and failure criteria for different groups (i.e. engineers emphasise functionality, customers emphasise convenience, stockholders emphasise profitability, social movements emphasise safety, etc.) [Braun, 1992]. This can lead to conflicting perspectives on the merits of a new technology. Considering ideas of built-in obsolescence in cars, the absence of a universal 'success' is illustrated through the impacts on sales and maintenance services of the hypothetical alternative; if a perfect car was manufactured that never broke down (which, depending on price, may be a perfect success for a driver), both manufacturers' and maintenance organisations' markets would be severely limited. Gooday contrasts this notion with ideas of *closure* put forward by Pinch & Bijker, where *all 'relevant social groups' agree about the appropriate form of a technology*, albeit for different reasons [Gooday, 1998, Pinch and Bijker, 1984].

This is illustrated by Pinch & Bijker's example of unequivocal consensus reached on the use of air-filled tyres for bicycles in the late 1890s, replacing the preceding solid rubber tyres. Gooday speculates that the finality of this closure may not be 'final', as there has recently been a resurgence of solid carbon fibre wheels on professional bikes [Gooday, 1998, Pinch and Bijker, 1984]. This also notes Anthony Strange's account of the 'Wisconsin' process for nitrogen fixation, resurrected following its abandonment in the 1950s [Stranges, 1992]. It may never be possible to say with certainty that a technological innovation has failed, due to the dynamic nature of science and technology [Gooday, 1998].

Taking these notions of non-linear development and complex social dependencies into account, this study focuses specifically on the second of Gooday's three failure conditions. Accordingly, failures are considered here in terms of the ever more demanding performance expectations that human users impose on their technologies, whilst the other two conditions are addressed to a greater extent in separate technology adoption modelling work. Specifically, the definition of technological failure used in this study is:

> "A point in time at which technology performance development stagnates/plateaus, with no further progressive trajectory improvements for a significant period of time, in comparison to the overall technology lifecycle. This is subsequently followed by the substitution of a new technology/architecture that is on a progressive trajectory"

This means that a technology is able to reach what could be observed as a temporary performance limit, before substitution to a new discontinuous technology occurs [Schilling and Esmundo, 2009] (i.e. most closely resembling the left and right images in Fig. 2.5).

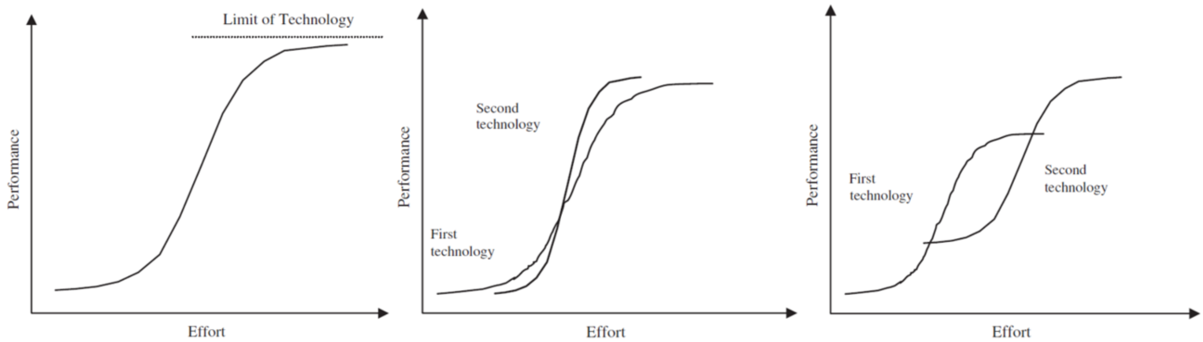


Figure 2.5: Classical S-curve models of technology development, and alternative substitution behaviours [Schilling and Esmundo, 2009]

This definition also follows from the work of Sood & Tellis, which applied a sub-sampling approach to analyse different types of 'multiple S-curves', and subsequently concluded that technologies tend to follow more of a step-function, with long periods of static performance interspersed with abrupt jumps in performance, rather than a classical S shape. However, this finding is still dependent on the specifics of the technology being considered. In this sense step-functions cannot be taken as an absolute rule either, but are possibly more representative of typical technological development patterns. In this study, stagnation periods were recorded where technology performance during a given sub-sample had an upper plateau longer than the immediately preceding growth phase, whilst the subsequent jump in performance in the year immediately after the plateau was almost double the performance gained during the entire plateau [Sood and Tellis, 2005]. Other studies, including the work of Chang and Schilling, classify multiple S-curves based on whether successive curves intersect or are disconnected (see Fig. 2.5 and [Chang and Baek, 2010, Schilling and Esmundo, 2009]).

2.2 Anomalies associated with scientific and technological crisis

When considering substitutions in science and technology, the concept of paradigms is often invoked [Kuhn, 1996]. These are the ideologies that shape the direction of thinking in these domains and, consequently, options considered to be the most likely candidates for successors to existing technologies. Conventionally it is assumed that technological paradigms are framed within scientific paradigms, meaning that the anticipated limits of a technology are formed by the extent of scientific theory at any given time. This implies that a technology cannot exceed observed scientific limits, although realistically this is not always the case, as in some areas technological development precedes scientific understanding. Examples here include the development of steam engines prior to thermodynamics, and recent developments in quantum computing and communication technologies. In any event, technological paradigms do not just represent a device or process by themselves, but more widely the practice, method, logic, infrastructure, and perception that supports a device or process, which are all governed by the science of the time [Constant, 1973]. Over time, technological paradigms are passed on as traditions of practice, with acceptance of the tradition bringing new individuals into the community, and inspiring growth [Constant, 1973]. As with scientific paradigms, technological paradigms experience periods of crisis that sometimes lead to substitutions and revolutions (when drastic changes are made to previously established logic), but both are largely dominated by normal or incremental processes for the majority of time.

Only substitution patterns arising from crises associated with technological failure have been discussed up until this point. However, previous studies have identified that technological substitutions are not just the result of the existing technology being deemed to have 'failed'. Edward Constant argued that a feature common to all technological revolutions is the emergence of *technological anomalies*, which can be traced to either scientific or technological crisis. In the work of Constant the first, and most common, cause of these technological anomalies was attributed to functional failure, where:

> "either the conventional paradigm proves inappropriate to "new or more stringent conditions", or an individual intuitively assumes that (s)he can produce a better or a new technological device" [Constant, 1973]

Conversely, technological anomalies were also identified as arising as a result of presumptive technological leaps:

> "The demarcation between functional-failure anomaly and presumptive anomaly is that presumptive anomaly is deduced from science before a new paradigm is formulated and that scientific deduction is the sole reason for the sole guide to new paradigm creation. No functional failure exists; an anomaly is presumed to exist, hence presumptive anomaly" [Constant, 1973]

To make presumptive technological leaps, individuals have to possess an understanding of the current rate of scientific advance (often not linked to their own field [Constant, 1973, Hughes et al., 1987], hence the description of these individuals between fields as 'cosmopolites' from Rogers [Rogers, 2010]), and the relative *extension opportunity* of technologies [Constant, 1973, Adner and Kapoor, 2015] (extension opportunities are discussed further in section 2.5). This means that they either are part of or exposed to the leading edge of a relevant scientific field (since visibility is required for insight or imitation, with confidence increasing as visibility improves [Dattée and Weil, 2007, Mäkinen et al., 2013, Rogers et al., 2005]), and secondly that they have to be uncommitted to the conventional technology [Constant, 1973]. However, two individuals in the same position, with the same level of commitment, may not reach the same conclusion, so an element of individuality and randomness is observed [Andolfatto and Smith, 2001]. Constant states that no link has been identified between the process of anomaly identification and the economic, social, or religious background of the individual, but this could be an interesting area for further exploration [Dattée and Weil, 2007]. This may relate to the opportunity available to individuals to act on resolving an anomaly, which may be different from a population's general awareness of the anomaly. Economic factors tend to have a direct link once initial concepts are formulated, as the uncertainty of transitioning between paradigms means financial estimates are unlikely to be accurate, and confidence is likely to be low for investment [Constant, 1973].

Lack of awareness can also allow presumptive leaps, as Constant cites for Frank Whittle's lack of knowledge about the prior turbojet invention of 1921 [Constant, 1973]. Equally, individuals will not always heed observations from scientific domains or other individuals even if aware of them. Work by Kuhn relating to decisions and beliefs based on local epoch-specific knowledge, suggests that even if a theory is ultimately correct, people will often reject it if there is not a supporting paradigm already in place at that time [Kuhn, 1996]. It could therefore be inferred that some form of credibility metric is required for both individuals and scientific domains to determine the likelihood that their messages are heeded. As the credibility of an individual, community, or domain increases, the likelihood that it will influence other entities increases. However, if the new paradigm is not properly developed or systems are not able to develop at a similar rate interdependently, resurgence of previous paradigms can also occur. This is seen from the resurgence of the conventional aeroengine paradigm in 1931 due to the development of supercharging and diesels [Constant, 1973, Rogers et al., 2005].

Constant suggests that technological anomalies that spur paradigm shifts most often result from technological failure, where an existing paradigm cannot meet new or more stringent conditions, or the result of ad-hoc intuition. Presumptive anomalies meanwhile, which are stated to occur less frequently, consider technological anomalies generated from quantifiable scientific insight into future limitations of foreseen failures, before a failure has occurred and a framework exists to support these anomalies [Constant, 1973]. Constant states that the insight has to be based on quantitative science to distinguish the anomaly from ad-hoc intuition and for it to spark a revolution (effectively converting supporters through evidence):

> "the scientific insight upon which the anomaly is founded must be expressible in quantitative form either as it comes from the science or as part of the new technological paradigm. The presumptive anomaly must be such that it is possible to tell whether or not a satisfactory solution is offered by a proposed alternative system. Because of the inherent and necessary resistance of technological communities to paradigmatic change, a new paradigm unsupported by quantitative evidence, however brilliant it might turn out to be, will stand little chance of timely adoption"

For the technological community to be persuaded to adopt, there has to be quantifiable evidence. It is not prescribed here how this evidence is manifested initially, but it might be assumed that by quantifiable science Constant is likely to be referring to deliberate external communications that are subsequently reiterated through *word-of-mouth* and peer effects. Scientific insights into a new technology usually tend to first appear as published hypotheses and conjecture, as opposed to socially exchanged user-experiences. Accordingly, the first indication of a new scientific insight is often found in deliberate communication mediums such as academic journals and marketing exercises, rather than social commentary. This follows from the assumption that presumptive insights are solely derived from scientific deduction [Constant, 1973]. However, the more recent impact of crowd-sourced support for scientific and technological developments could be an interesting challenge to the assertion of quantifiable evidence as a prerequisite. It is also questionable whether Constant considered only the elementary sciences as capable of identifying future limits [Henderson, 1995], or whether these could instead originate from social sciences or other community driven domains. For example, societal limits may play a role in either bringing to attention, or reinforcing, concepts such as sustainability that are subject to both hard and soft scientific constraints [Ruttan et al., 2008]. In a modern sense, the social and environmental sustainability of petrochemical-based infrastructure could be considered a candidate presumptive anomaly, as predictions of fuel price spikes, expected and unexpected fuel shortages, and mounting social pressure are already envisaged. It is also interesting to note that Constant, in a similar fashion to Kuhn, believed that resistance to moving away from 'normal technology' (i.e. incremental innovation) is essential to avoid a chaotic dispersion of effort in technological ventures [Constant, 1973, Kuhn, 1996]. This subsequently precludes identifying significant value (both economic and otherwise) derived from off-shoots of more chaotic exploration styles.

Whilst technological substitutions and revolutions may originate from either scientific or technological crisis, a critical area of commonality lies in the anomaly-crisis process observed in both conditions:

> "in both science and technology anomaly causes certain individuals to reject the conventional paradigm and to create new paradigms, and, in each, crisis may lead to revolution" [Constant, 1973]

The type of crisis that emerges is dependent on which type of anomaly precedes it. Scientific crisis can occur irrespective of whether an alternative theoretical framework exists or not when a persistent, unresolved, scientific anomaly successfully refutes an established theory [Constant, 1973]. This crisis is directly linked to the anomaly, with direct implications for all related theories and community members. However, technological anomaly and crisis are rarely so logically driven, and can arise where existing technological paradigms are still performing favourably. This is illustrated by the turbojet revolution of the 1930s and 1940s, where piston-engine developments provided remarkable performance improvements and continuing success, but were superseded by scientific predictions of a performance limit arising from propeller compressibility effects. Consequently scientific foresight was directly responsible for the radical technological changes that followed [Constant, 1973]. In addition, for a technological anomaly to provoke a technological crisis, a convincing alternative paradigm must exist, so that the relative functional failure of the conventional system is observable [Constant, 1973]. If an alternative does not exist, then the broader community impact is not generally visible, in contrast to scientific crises. This is because different combinatorial implementations of a technology can lead to easy dismissal of an individual technological failure, or ad-hoc improvement [Constant, 1973]. This means that technological crises do not appear due to the persistence of anomalies alone [Constant, 1973], whilst the origin and nature of anomalies are fundamentally different between science and technology. In technological crises, anomalies are always hardware or object focused, and are not determined relative to the same phenomenological insights that are perceived by science. Furthermore, individuals triggering the crisis are generally not looking to create a new paradigm, but a new device or process that creates a new paradigm as a by-product. However, these individuals might require significant resources and investment to create a supporting framework, which may not be available for smaller entities (e.g. consolidation of turbojet pioneers into larger organisations before mass-production [Constant, 1973]). The alternative technological paradigm instigates the crisis, whilst the technological anomaly may only be seen as speculation or a limiting condition to the normal technology [Constant, 1973].

2.3 Technological revolutions and General Purpose Technologies

When a crisis achieves a certain critical mass, the possibility of technological substitution, or even revolution, becomes more substantial. Prior to this however, exists a period of *normal science*. In these circumstances, as technology is always considered to be lacking in comparison to science's theoretical conjectures, a steady, profitable, drive of incremental innovation takes place to narrow the gap. Henderson describes optical lithography as illustrating the persistence of incremental innovation and deficiencies of traditional dominant design and life cycle models for determining technological limitations [Henderson, 1995]. Conversely, science often takes a more sporadic approach to progress. Constant states that during periods of *normal science*, patenting and investment tends to increase notably. By contrast, during the period leading to a technological paradigm shift, investment in a new framework is often seen as risky, and patenting can be a low-priority activity (as illustrated by Frank Whittle's elaborate turbojet patents in 1940, following the lapse in 1935 of his original 1930 patent that could have been renewed for £5 [Constant, 1973]). Periods of significant investment and patenting cannot therefore be used alone as an indicator of revolutionary change. However, when *normal technology* is no longer maintaining the same economic progress and more radical paths are signifying potentially larger economic gains, market dynamics can give the final push needed for a revolution (more so than in science [Constant, 1973]). This is supported by more recent studies of product and process innovations which have observed distinctions between *sustaining* and *disruptive* innovations, as characterised by the different origins and rates of technology development shown in Fig. 2.6 and Fig. 2.7.

These studies note that disruptions occur when small companies, with fewer resources, are able to successfully challenge established incumbent businesses [Christensen et al., 2015]. In this view, incumbent organisations focus on improvements targeted at the most demanding, high-end, segment of the market, whilst overlooking lower performance or potential new-market segments [Christensen et al., 2015]. These overlooked market segments are targeted by disruptive entrants who attempt to gain a foothold, often at lower prices, before starting to move upmarket into regions of mainstream performance expectations [Christensen et al., 2015]. If the rate of development observed for a new entrant is significantly greater than the rate of development arising from incumbents' sustaining performance improvements (as illustrated in Fig. 2.7) then these market dynamics can support the need for revolutionary shifts in technologies and supporting ecosystems.

Once a technological revolution begins, emphasis shifts from normal science *puzzle solving* behaviours to *puzzle definition* traits, where individuals seek to redefine technological rules in a manner that fits

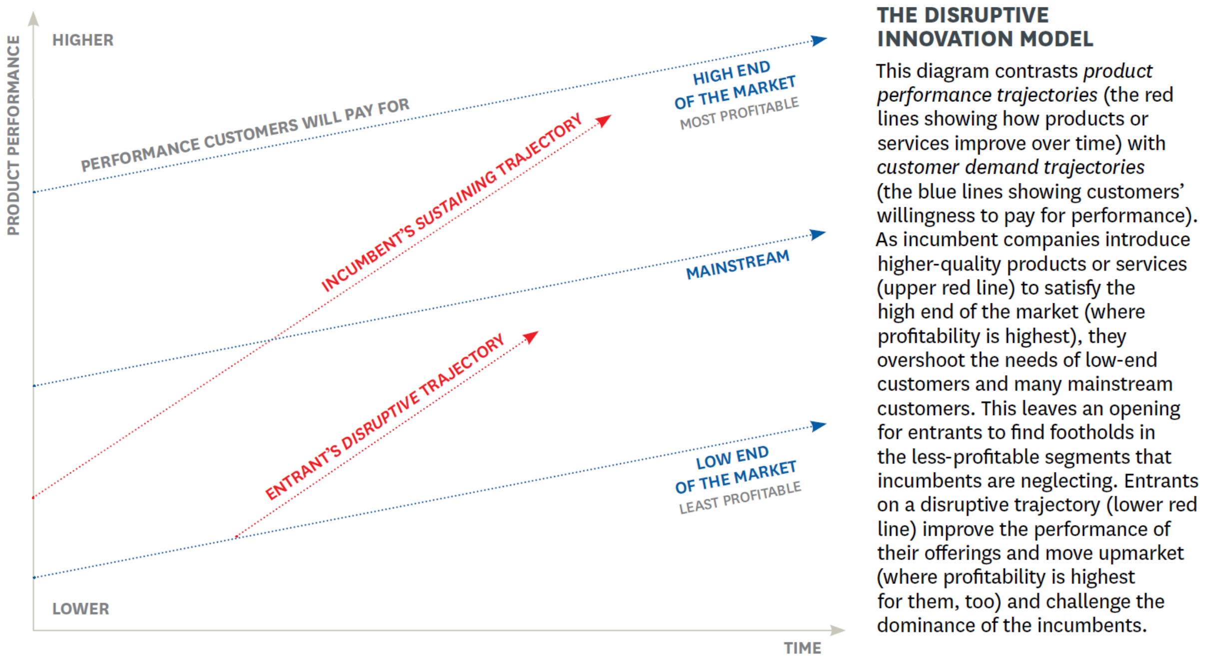


Figure 2.6: The disruptive innovation model [Christensen et al., 2015]

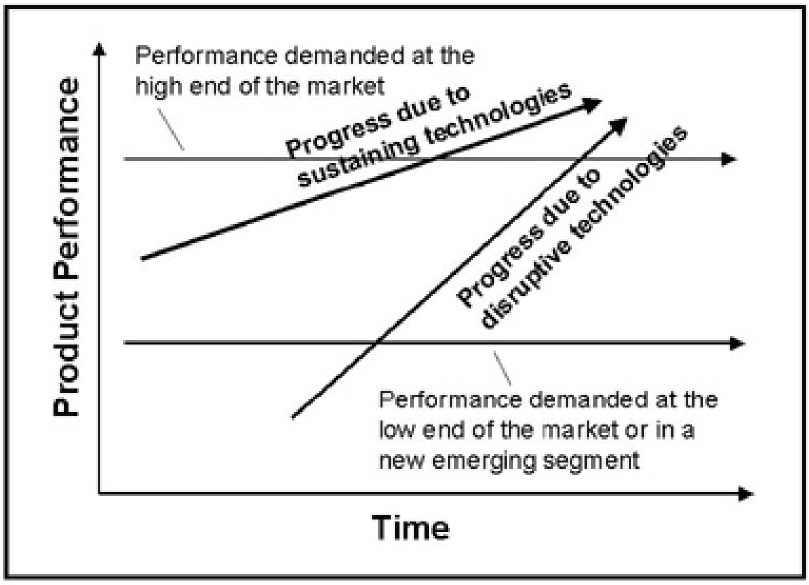


Figure 2.7: Disruptive innovation on a trajectory to overtake sustaining technologies [Christensen, 2013]

both the current persistent anomalies and the previously solved puzzles [Constant, 1973]. In Constant's model of technological revolution, a critical mass is required for the revolution to occur, defined by when a significant minority of the population adopts a new paradigm, enabling the spread (i.e. imitation) across the population to become self-sustaining, to the point where the rest of the community rapidly adopts [Constant, 1973, Rogers et al., 2005]. Once a critical mass occurs, self-organising and emergent adoptive behaviours are observed at the system level, the rate of adoption is no longer linear in nature, and innovation diffusion is no longer limited to local connections [Rogers et al., 2005]. To achieve this critical mass, only a small number of individuals need to demonstrate significant success with the new approach [Constant, 1973]. This may occur when stakeholders with large power or influence bases adopt the new technology (e.g. the Air Ministry's adoption of Whittle's turbojet [Constant, 1973]). After this point, critical mass clusters around and imitates the opinion leaders, as empirically observed in the STOP AIDS programme [Rogers et al., 2005]. A network representation of this revolution process is presented in chapter 3.

Beyond the routine technology substitutions that occur, General Purpose Technologies (GPTs), such as electric power, telecommunications, and nanotechnology, are identified as technologies that emerge from revolutions, which lead to new phases of incremental innovation [Ruttan et al., 2008]. These technologies are pervasive (i.e. have an impact on technical change and productivity across many industries), are capable of being continuously refined and improved (becoming cheaper and more efficient with development), and spawn new product and process innovations across the affected industries. Previously, many of these technologies emerged with the aid of significant public funding or as part of military research activities, but public-commercial consortiums are now potentially driving the development of GPTs [Ruttan et al., 2008]. Many of the technologies considered in subsequent chapters, such as renewable energy, the internet, and wireless data transfer, could potentially be seen as GPTs. Indications of the maturity of a GPT and potential switch to a new technology are seen in consumers' lack of interest to buy a product offering, the consolidation of existing companies producing the GPT, and increasing concern about the sustainability of productivity gains from the technology [Ruttan et al., 2008]. However, this also applies to some extent to more routine technological substitutions.

2.4 Large technological systems

Placing technological substitutions in the dynamic context of the individuals, societies, organisations, and disciplines that build them greatly improves the understanding of causality behind these events. Accordingly, Thomas Hughes produced a compelling narrative of the formative characteristics and patterns observed in the evolution of Large Technological Systems (LTS) in his study of the same name [Hughes et al., 1987], providing relevant insights into the emergence of competing technologies. In this work Hughes outlines the role of *System Builders*, who are individuals or organisations that have sufficient experience across a broad range of domains to create new structures (technical and organisational) to unite otherwise dissonant systems and entities together into a cohesive technological framework. This is a creative activity, but may also involve destruction of prior existing frameworks [Hughes et al., 1987], as may be the case in substitutions.

Four System Builder types are proposed within this discussion, each with a different motivational focus for the system: inventor-entrepreneurs, manager-entrepreneurs, financial entrepreneurs, and consulting engineers. Following Braun's recognition that success and failure criteria vary greatly depending on the groups involved (see section 2.1), this implies that numerous different directions can be taken in the development of new technological systems based on the specific goals of the creative group. In addition to the directional uncertainty that these alternative goals present, when considering open technological systems, two kinds of environment can be considered: environments upon which the system depends, and environments dependent upon the technological system. In both, Hughes proposes that there is a one-way flow of influence from one environment to the other, but no interaction [Hughes et al., 1987]. Consequently, as technological systems evolve, Hughes concludes that they increasingly manage to incorporate more of their environment within them, to eliminate sources of uncertainty originally outside their control [Hughes et al., 1987].

Humans play a key role in providing feedback on the system performance as this evolution takes place, and continually act to correct errors as they appear [Hughes et al., 1987]. Equally, as organisers and managers of large technological systems often prefer a hierarchical structure to ensure control, as systems evolve they often become more structured, bureaucratic, and less adaptable [Hughes et al., 1987]. Mäkinen characterises these structures as being hierarchically nested and composed of smaller sub-systems, which operate interdependently across their own and other hierarchical system levels, and are goal-seeking at both the sub-system and holistic levels [Mäkinen et al., 2013]. As a result, when new technologies begin to be adopted, this can create a performance gap between sub-systems which leads to a noticeable potential difference and greater incentive for adoption. Additionally, repeated evidence of links between components in an LTS often indicates systematic interactions between these components, where changes in the policy or strategy of one sub-system are likely to have an impact on the policy and strategy of others [Hughes et al., 1987].

Hughes describes this evolutionary pattern as a reverse salient: a persisting pocket of resistance on a battlefield that exists once a battle front has advanced past it (i.e. a protrusion back from the main line). Technologically, this is a lingering area of performance that is holding back the rest of the system, or a persisting anomaly not yet accommodated by the new paradigm. To progress further, the reverse salient must first be corrected, so communities of inventors congregate around these points. If a reverse salient cannot be resolved with the current paradigm, then it can lend support to more radical frameworks and support presumptive anomalies [Hughes et al., 1987]. When existing solutions are not able to remedy this performance gap, this is consistent with the notion of observable functional-failure proposed by Constant [Constant, 1973]. However, in order to identify these reverse salients, it is necessary to consider the technological system's boundaries that define user expectations, which in Hughes' model are specified as the limits of control exercised by artificial and human operators [Hughes et al., 1987]. This boundary definition potentially does not reflect the important distinction between control and influence, as it assumes technological systems do not have to take responsibility for areas that are directly outside their control, but might be within their influence. However, from a point of view of ensuring a tractable solution to technological development requirements, it is still a reasonable assumption to take.

Hughes goes on to outline seven stages that technological systems experience during their evolution. These are invention, development, innovation, transfer, growth, competition, and consolidation [Hughes et al., 1987]. Systems can move between these in a non-sequential and potentially backtracking fashion, or may repeat phases as the momentum of the system changes. Considering the first of these phases in relation to Constant's model of technological revolutions, individuals could perceive new inventions to be anomalies observed in other scientific and technological fields [Constant, 1973]. Following this, during the development phase, observations of the efforts dedicated to building scientific and technological knowledge beyond that extracted from the original invention provide a means to gauge the relative maturity and commercial viability of the new technology. Phases of innovative development then begin to appear as the emergent technology is coupled with known technical and commercial solutions from outside of the original field of discovery, to address reverse salients holding back continued development. As the new technology starts to become transferable to other disciplines, demonstrating wider commercial applicability beyond the original requirements, it encourages more individuals to adopt the same technological framework. A non-linear cascading of adopters takes place across different hierarchical layers during subsequent periods of growth [Rogers et al., 2005], which stimulates competition from alternative technological paradigms that now recognise the transition taking place. This corresponds to the achievement of critical mass as described by Constant [Constant, 1973]. Lastly in periods of consolidation, a dominant technological system emerges as industry converges on the most widely accepted form of the new technology, often coupled with a series of acquisitions and mergers between competing organisations [Hughes et al., 1987]. Taken in the context of Kuhn and Constant's descriptions of scientific and technological revolutions, periods of consolidation would align with phases of *normal science*, when functional-failure anomalies may again become less apparent to invested industries [Kuhn, 1996, Constant, 1973].

Considering evolution as a whole based on these stages, analogies to both motion and momentum can be made for technological systems to describe their accumulation of mass over time [Hughes et al., 1987]. This refers to the collection of subsystems, entities, and other organisational components that systems acquire as they advance, with growth rates of the system often being depicted as a velocity. The durability of previous artefacts and knowledge also gives rise to the idea of a trajectory throughout this process [Hughes et al., 1987, David, 1991]. Consequently, Hughes believes that assigning momentum to an LTS is a more accurate reflection of observed behaviours than to assign the concept of autonomy to the same system, as the latter implies a limited social construction of the technological system [Hughes et al., 1987].

Depending on their period of introduction, inventions can take several forms [Hughes et al., 1987], which can in turn have major repercussions for the skill sets required in technological systems following a substitution. Radical inventions, introduced during the invention stage, often reduce the value of employees' skills trained in the existing paradigm (i.e. deskill), counteract financial investments, and stimulate anxiety in large organisations [Hughes et al., 1987]. Opposed to this are conservative inventions, which are normally introduced during subsequent periods of growth and competition, but have a much more muted effect on the distribution of skill sets [Hughes et al., 1987].

The implication of different invention types was explored in more detail using a Systems Dynamics model in the work of Andolfatto, where the impact these disruptions have on population skills distributions in LTS was tested. This experimentation concluded that either neutral shocks or skill-biased technology shocks will result [Andolfatto and Smith, 2001]. In the case of neutral shocks, population skill sets are not required to be redistributed as productivity across skilled and unskilled sectors is affected evenly, whereas in the latter condition individuals seek training to match the redistribution of skills now required [Andolfatto and Smith, 2001]. Neutral shocks result in a steady state that is more characteristic of incremental technology improvement, where there are largely unchanged sectoral employment levels, increased sectoral and aggregate output, increased sectoral productivity, largely unchanged skills premiums, and increased wages as a result of greater efficiency. During transition, neutral shocks produce a decline in overall aggregate and sectoral employment, as well as corresponding output levels, whilst productivity temporarily increases in the unskilled sector (and vice versa for the skilled sector), coupled with a decline in the overall skill premium [Andolfatto and Smith, 2001]. By contrast, skill-biased technological improvements were found to lead to steady states that were more characteristic of technology revolutions. In this scenario, there is an increase in skilled employment and training, a decrease in unskilled and aggregate levels of employment, an increase in skilled output, a skill premium that is notably different to that prior to the disruption, and an increase in wages from greater efficiency [Andolfatto and Smith, 2001]. On some occasions these shocks result in previously skilled employees having to retrain at the risk of being otherwise classed as unskilled, and conversely, previously unskilled employees may now demonstrate skill profiles putting them in a more favourable position.

Within Andolfatto's dynamics model, the overall global skill capability is kept constant at an aggregate level (i.e. zero-sum game based on Schumpeter's hypothesis that for every act of creation there is also an act of destruction [Schumpeter, 2010]), but individual skill values in each discipline are reassigned as a result of this change. This results in a temporary loss of production during the transition (as predicted from historical observations), as skilled workers are now no longer as effective (i.e. the market devalues their skill or fitness [Dattée and Weil, 2007, Rogers et al., 2005]), and previously unskilled workers leave posts to seek training to benefit from the shift in their favour [Andolfatto and Smith, 2001]. Andolfatto's model therefore predicts the income levels of workers and sector productivity, as workers transition between skilled, unskilled, and learning sectors, based on their awareness of the value of their abilities, using three dynamic value functions. Unlike Constant, Andolfatto assumes workers attach zero probability to paradigm shifts occurring, whereas the historical examples provided in [Constant, 1973] show that some individuals often have foresight of these shifts before they take place. The assumption of equal and opposite skill set redistribution may not be realistic (as the source population will grow or contract outside of the market supply and demand variation, and may not be able to pick up skills lost in another region), and the assumption that personal value for workers will always be determined from a purely economic perspective. However, this model presents a helpful starting point for assessing the dynamics in LTS during and following a substitution.

2.5 Modes of substitution

Building on the works of Constant, Schilling, and Sood, a conceptual framework for analysing technology substitutions was published by Ron Adner that considers both the *emergence challenges* facing new technologies and the *extension opportunities* still available to existing technologies (see Fig. 2.8 [Adner and Kapoor, 2015]).

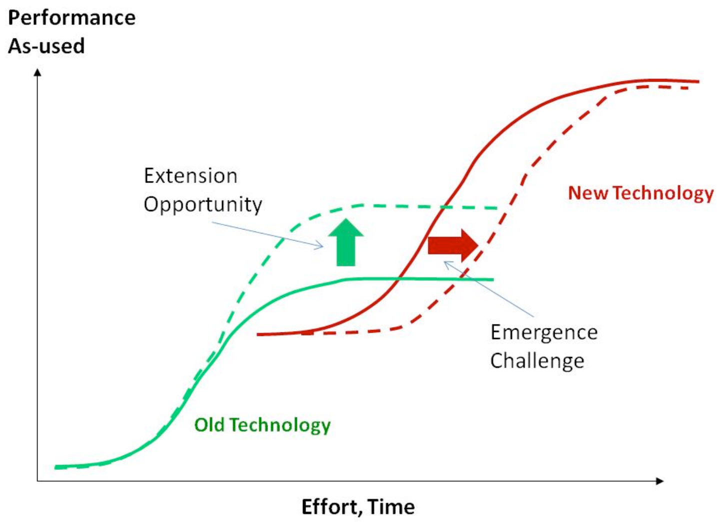


Figure 2.8: Dimensions considered in Adner's technology substitution framework [Adner and Kapoor, 2015]

In this, four substitution regimes are proposed, considering high and low scenarios for both new technology emergence challenges and old technology extension opportunities, and are demonstrated in the context of developments in semiconductor lithography equipment. These regimes are characterised as 1) *Creative Destruction* (low extension opportunity and low emergence challenge), 2) *Robust Coexistence* (high extension opportunity and low emergence challenge), 3) *Resilience Illusion* (low extension opportunity and high emergence challenge), and 4) *Robust Resilience* (high extension opportunity and high emergence challenge).

The names allocated to these regimes are descriptive of the market share characteristics observed for each. *Creative destruction* represents the fastest substitution mechanism, with the unhindered emergence of the new technology leading to the rapid market downfall of the already weak existing technology. *Robust coexistence* corresponds to the intense competition that occurs when new and old technologies have few obstacles to continued development, leading to a prolonged period of coexistence as both improve steadily before substitution eventually takes place. In contrast, *resilience illusion* initially depicts a largely stagnant market dominated by the incumbent technology, until the emergence challenges associated with the new technology are finally resolved. At this point the existing technology's fragility is exposed, leading then to a rapid transition. Lastly, in *robust resilience*, meagre performance improvements in the new technology are consistently outpaced by the extension opportunities presented by the old technology, leading to a picture of an emergent technology that seems revolutionary initially, but is ultimately over-hyped. These substitution regimes are illustrated in Fig. 2.9.

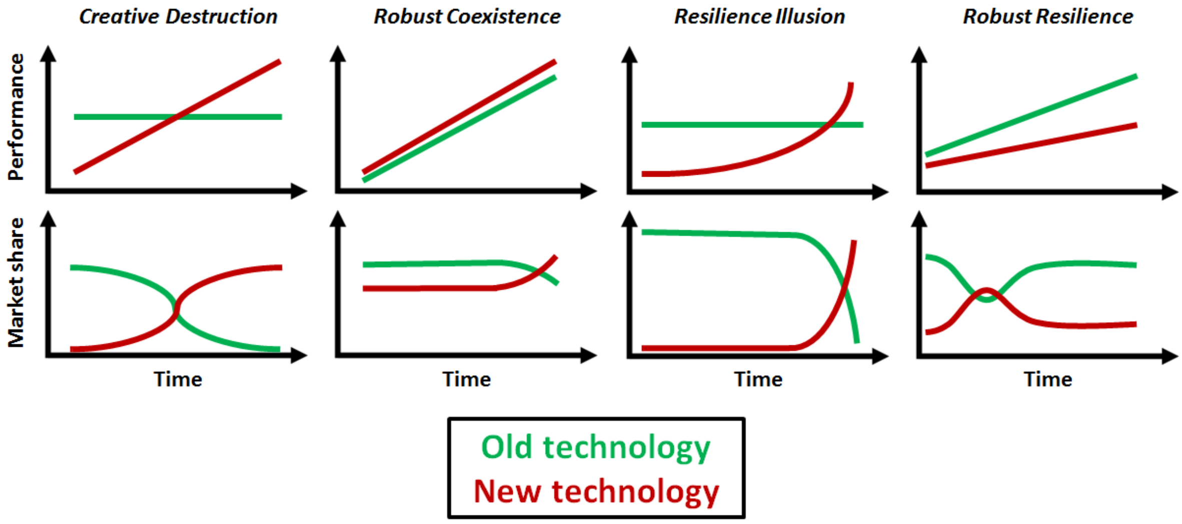


Figure 2.9: Illustration of substitution regimes, based on Adner's framework

Based on the definitions of functional failure and presumptive anomaly described in sections 2.1 and 2.2, reactive technology substitutions are assumed here to correspond to quadrants 1 and 3 in Adner's substitution framework (i.e. substitutions based on low extension opportunities for existing technologies), whilst presumptive technology substitutions are thought to correspond to quadrants 2 and 4 (i.e. substitutions where there still appears to be high extension opportunities for existing technologies). This means that for presumptive substitutions some form of scientific foresight is required to lead to the development of a new technology prior to the stagnation of the existing technology, since the development potential of the incumbent is still high. Conversely, reactive substitutions occur as a result of a technology failing to meet current performance expectations. Further details and examples of these technological substitution regimes are provided in [Adner and Kapoor, 2015] along with a review of the corresponding technology adoption S-curves.

The current study only considers the *extension opportunity* dimension in its classification of substitution modes, to facilitate the development of the data-driven methodology presented here. This analysis could be repeated and decomposed further into the four higher fidelity regimes proposed by Adner, but this would require additional case studies to ensure a sufficient number of technologies are available in each category, whilst also requiring supplementary literature or expert evidence to support category assignments. For this reason, this study only considers the ability to distinguish between the two broader *extension opportunity* driven modes of substitution (i.e. reactive or presumptive) from analysis of historical scientific and technological data. Whilst the higher level modes considered here are characterised by low and high *extension opportunity* scenarios respectively at the tail end of the existing technology's S-curve, variability in the *emergence challenge* dimension is assumed to slow the development of the new technology at the start of the subsequent S-curve. *Emergence challenges* often relate to either the degree of complementary technologies available to support the new technology, or the extent of existing technology lock-in effects on potential adopters [Jeong et al., 2016], resulting in radical technologies often encountering long delays in adoption [Farzin et al., 1998]. Consequently, this dimension varies the initial curvature of the new technology's S-curve, rather than shifting in time the point of first emergence (which for this analysis is effectively treated as a static point). In terms of performance trends, this means that a reactive substitution corresponds to a period of performance stagnation prior to the new technology first appearing. In cases where existing technology development has been completely terminated first, this is referred to as a gradual substitution in [Jeong et al., 2016]. Conversely, a presumptive substitution corresponds to the new technology first emerging as the existing technology continues to improve. This is illustrated in Fig. 2.10.

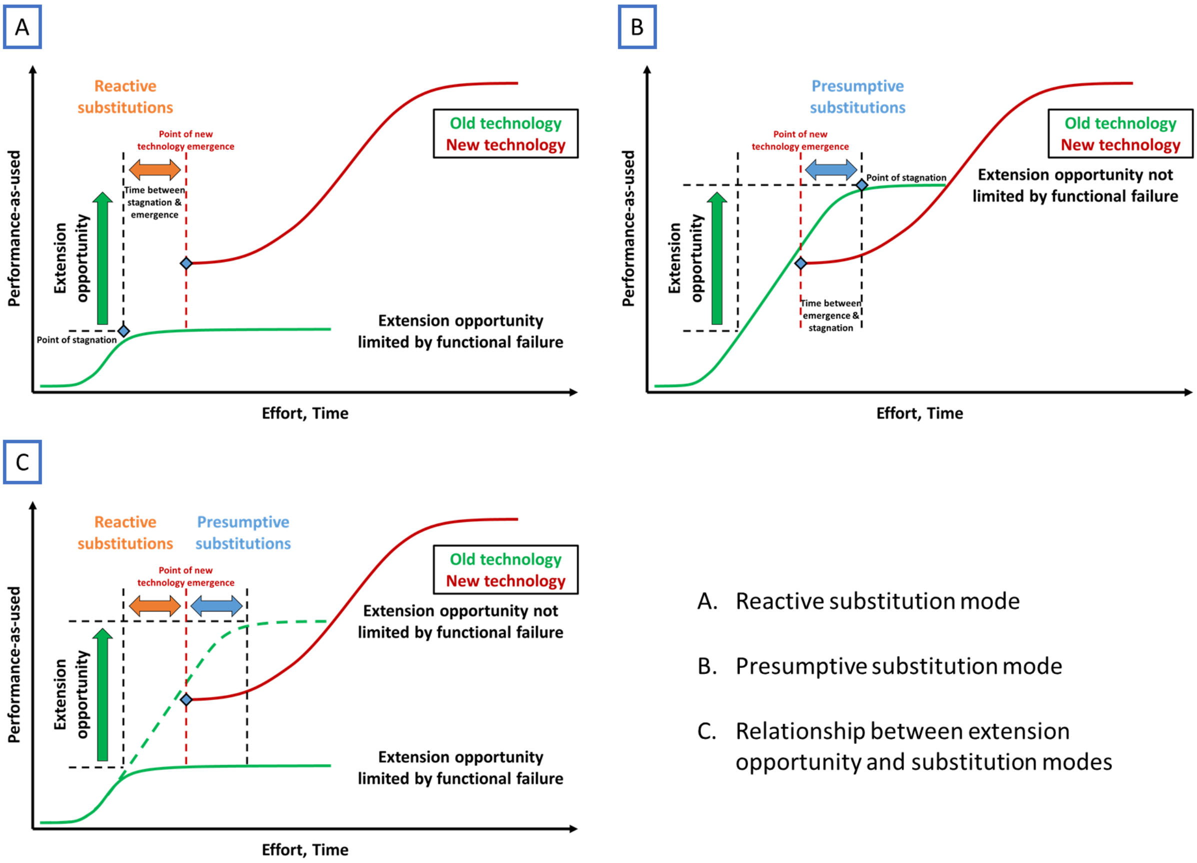


Figure 2.10: Illustration of reactive and presumptive substitution modes, based on Adner's framework

Table 2.2 uses Adner's framework, alongside the definitions provided in sections 2.1 and 2.2, with performance evidence obtained from literature, to classify a sample set of technologies according to broader modes of substitution observed.

The examples in Table 2.2 show that neither reactive of presumptive transition types are constrained to specific industries. Instead both substitution types have been observed across a wide range of industries since the late 18th century (and potentially throughout the history of technological innovation, although evidence for identifying substitution modes becomes harder to find prior to this). Equally, the examples in Table 2.2 suggest that substitution modes may change from one generation of technology to the next

Table 2.2: Identified examples of reactive and presumptive technological substitutions

Examples of reactive substitutions	Examples of presumptive substitutions
Plug-compatible market (PCM) disk drives [Christensen and Rosenbloom, 1995]	Transition from piston to jet engines [Constant, 1973, Chang and Baek, 2010, Smil, 2004]
Transition to fibre optic cables from Cu/Al wires for data transfer [Sood and Tellis, 2005]	Transition to optical undersea cables from coaxial cables [Chang and Baek, 2010]
Transition to Low Pressure Sodium lights from Tungsten Filament Lamps [Chang and Baek, 2010]	Transition to water turbines from steam engines [Constant, 1973, Smil, 2004]
Transition to Compact Fluorescent Lamps from Tungsten Filament Lamps [Chang and Baek, 2010]	Transition to early gas engines from steam engines [Constant, 1973, Smil, 2004]
Transition to White LED lighting from Low Pressure Sodium and Compact Fluorescent Lamps [Chang and Baek, 2010]	Transition to steam turbines from water turbines [Constant, 1973, Smil, 2004]
Transition to hypersonic aircraft from supersonic [Chang and Baek, 2010]	Transition to catalytic petroleum cracking from thermal cracking [Constant, 1973]
Transition to coaxial undersea cables from single cable [Chang and Baek, 2010]	Transition to transistors from the vacuum tube [Foster, 1985]
Transition to T-carrier system from modem internet access [Chang and Baek, 2010]	Transition to atomic energy from fossil fuels [Constant, 1973, Graus and Worrell, 2009]
Transition to Synchronous Optical Networking (SONET) system from T-carrier internet access [Chang and Baek, 2010]	Renewable energy sources: transition to solar PV/thermal, wind, geothermal, hydropower, and marine energy from fossil fuels [Graus and Worrell, 2009, Smil, 2004]
Transition to ink jet and laser printers from dot matrix printers [Sood and Tellis, 2005]	Transition to modern battery and plug-in hybrid electric vehicles from petrol and diesel vehicles [Zachariadis, 2006]

for the same application. This can be seen in the contrast between the reactive substitution observed in the transition from single to coaxial undersea cables, followed later by the presumptive transition to optical cables.

With any technology, many different facets exist that can describe how the technology performs. In this sense, performance metrics that define technology development S-curves are not standardised and vary depending on the historical era considered or the maturity of the product being offered. Consequently it is possible to define multiple performance S-curves for any given technology depending on the performance features of interest [Sood and Tellis, 2005]. However, prior studies have identified that progress and competition occur systematically along a primary performance dimension based on product functionality first before moving, generally less systematically, into performance dimensions related to reliability, convenience, and cost [Christensen, 1999, Sood and Tellis, 2005]. In the broader context of technological substitutions it therefore follows that functionality-based performance metrics provide the best basis for mapping against the technology development S-curve [Sood and Tellis, 2005]. These key metrics are also usually predominant in historical narratives describing technological transitions for the decisive roles each played in influencing adopters. A review of the dominant performance trends for different industries consequently provides a more realistic insight into the relationships between performance expectations, scientific foresight, and observed substitution type. The performance evidence supporting the classifications in Table 2.2 and those in later chapters is therefore presented in the following sections for each technology group considered (further details of events and sources are in chapters 5, 6, and Appendix A). These historical trends describe the state of the incumbent technology, in each domain considered, at the point where an emerging technology first appeared. More specifically, the following sections consider whether the key performance metric of the incumbent technology was seen to be noticeably improving or stagnant at this time, and use this as the basis for classification.

2.5.1 Domestic lighting technologies

The 'Lumens per watt' (i.e. luminous efficacy) measure of performance is used here to classify the various lighting technologies included in Table 2.2 and later in this study. Considering first the original incandescent lamps invented in 1878 that subsequently revolutionised electric lighting, these appear to have arrived whilst their predecessor, gas lamps, were still improving. This is shown in Fig. 2.11, but is clearer in the data presented in Appendix B of [Chang and Baek, 2010], which suggests that gas lamps improved steadily between 1827 and 1916. In parallel, kerosene lamps seem to have been continuously improving during this time [Chang and Baek, 2010]. However, both gas and kerosene lamps provided inconsistent levels of brightness (continually flickering), gave off nauseous smells, where complex to use, and required technical skill to clean and maintain [Freeberg, 2013]. In this sense, end-user functionality measures were key in displacing gas lighting, along with the promise of more versatile applications. However, Thomas Edison's goal of constructing "central station" power plants that would generate and distribute electricity from large dynamos across wired networks was based on the insight that this would revolutionise not just electric lighting, but subsequently power motors and other machinery in a manner that gas could not [Pool, 1997]. As a result, it is possible to conclude that the introduction of incandescent lights was the result of a presumptive leap, although the lack of data makes this assumption difficult to verify from the data alone.

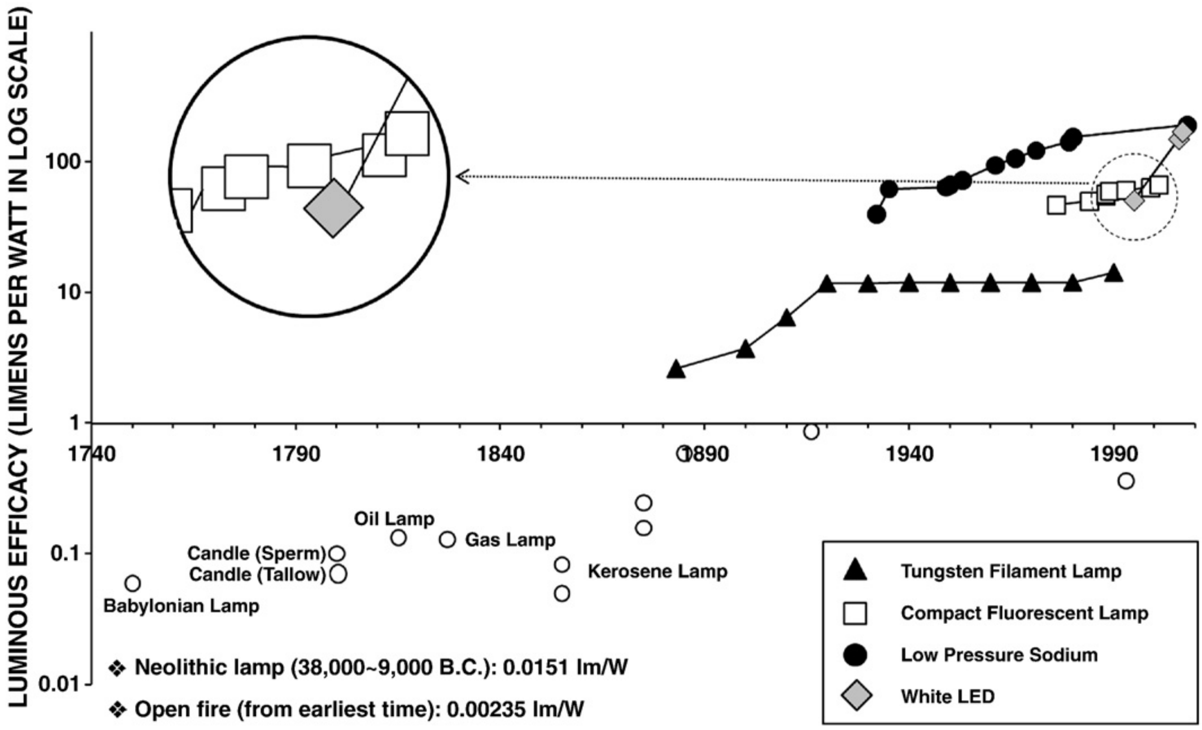


Figure 2.11: Historical evolution of lighting efficacy, 1740 - 2010 [Chang and Baek, 2010]

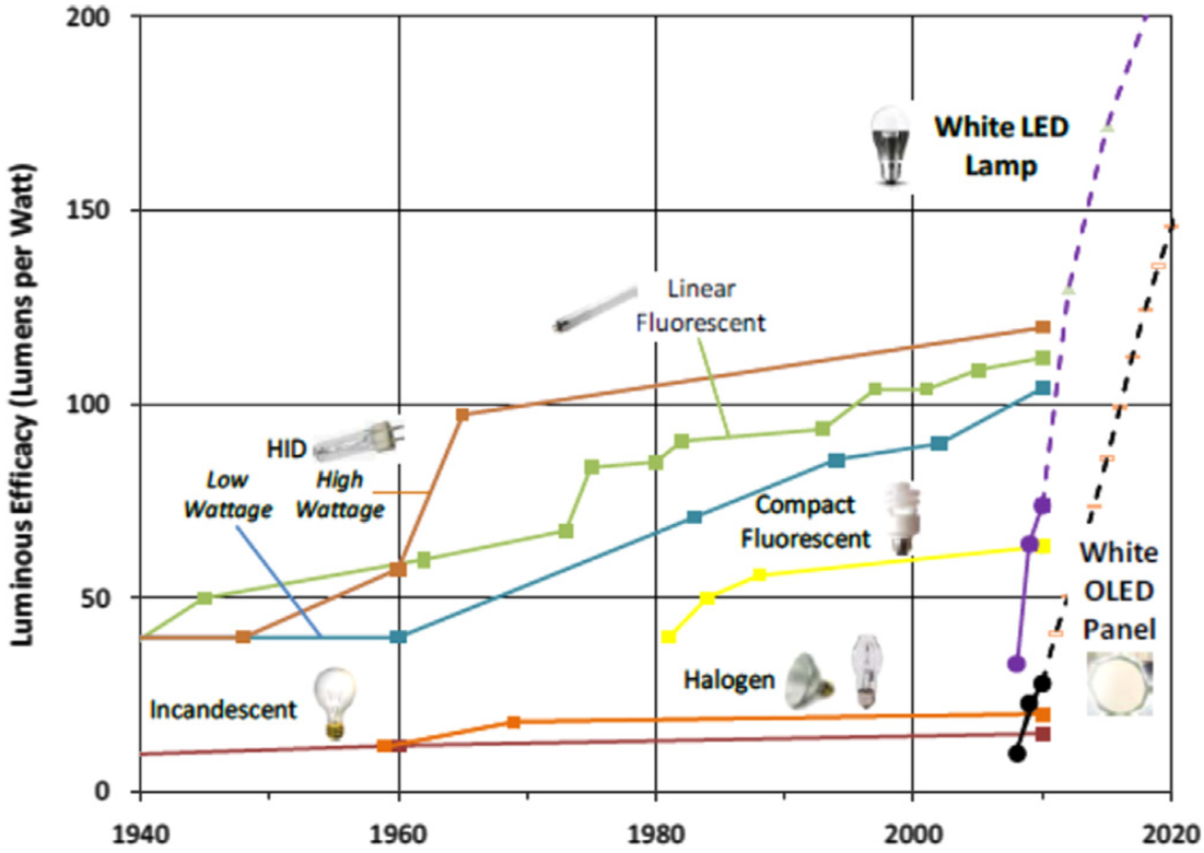


Figure 2.12: Historical and predicted evolution of lighting efficacy, 1940 - 2020 [Almeida et al., 2014]

Following this transition to electric lighting, data compiled by Chang from multiple sources reveals that the luminous efficacy of tungsten filament lighting effectively stagnated after 1920, and has remained relatively unchanged since [Chang and Baek, 2010]. This is seen more clearly from the data presented in Appendix B of [Chang and Baek, 2010], along with Fig. 2.11 and Fig. 2.12. This was eventually followed by the emergence of Linear Fluorescent Tube (LFT) lights in the late 1930s. The first commercially successful fluorescent lamps for advertising (not general illumination) were patented by Jacques Risler in 1926, with general illumination credited to Arthur Compton and George E. Inman in 1934, although this is contended by a 1927 patent filed by Meyer, Spanner, and Germer in Germany [Bright, 1949, H. A. W, 1931, Germer et al., 1939]. Low-pressure sodium lights improved steadily between approximately 1935 and 1990 (see Fig. 2.11), however these are typically used outdoors rather than indoors, and so at this time incandescent lights were the prevalent technology for residential buildings. Similarly, high-pressure mercury lights were relatively stagnant between about 1935 and 1950 (see Fig. 2.13), and are primarily used for large commercial building or outdoor lighting. In this sense, the development of fluorescent lamps for indoor applications would appear more reactionary than presumptive.

Halogen lighting can be seen from Fig. 2.12 to have emerged in 1959 (the year of first invention) following the same stagnation of incandescent (i.e. tungsten filament) lights. Whilst LFT lighting steadily improved between 1950 and 1960, these lights were typically used in commercial rather than

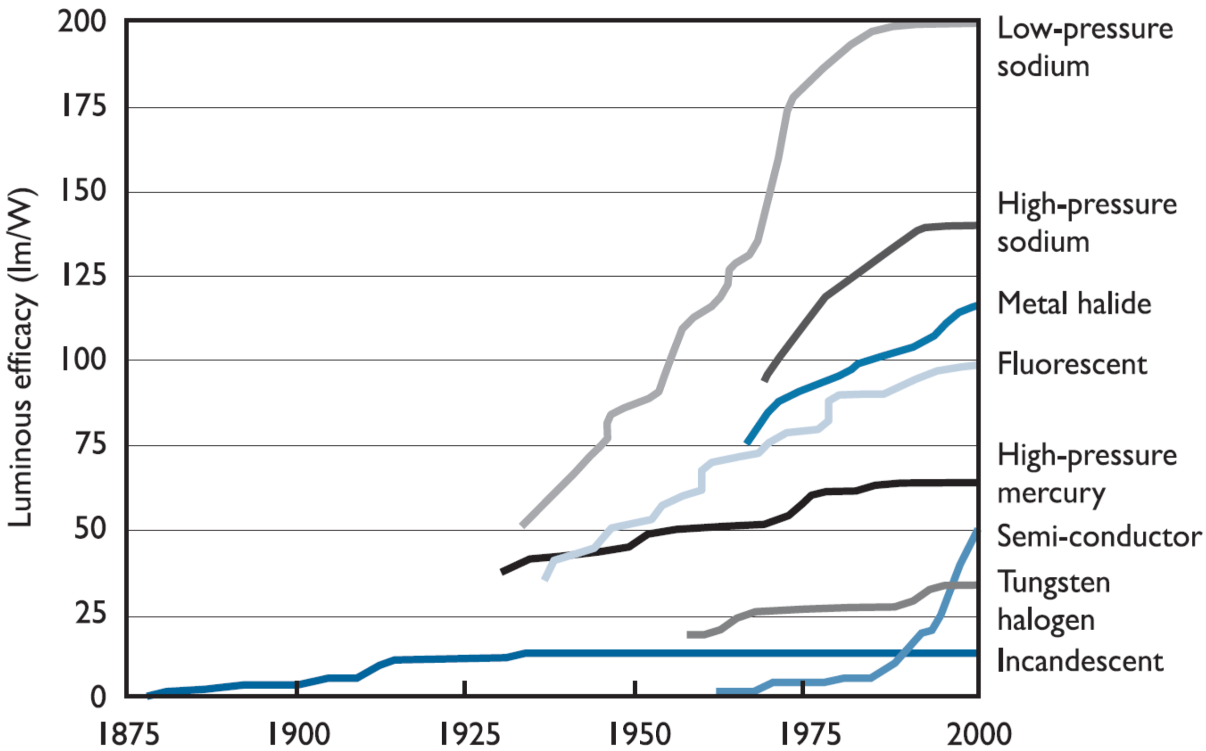


Figure 2.13: Historical evolution of lighting efficacy, 1875 - 2000 [Waide et al., 2006]

residential buildings, and so at this time incandescent lights were still the prevalent technology for residential buildings. Similarly, low and high-pressure sodium lights are for outdoor use, so again not considered for indoor lighting purposes. This agrees with the longer-term trends shown in Fig. 2.13, and so halogens appear to have filled a reactive need within the residential market.

Halogen lighting is seen to stagnate from the late 1960s in Fig. 2.12. This suggests that the introduction of CFLs as indoor lighting in 1976 followed preceding functional failures in both incandescents and halogens. More recently, CFLs have begun to suffer the same fate. A relatively stagnant period between 1988 and 2010 (see Appendix B in Chang and Baek [2010] and Fig. 2.12) preceded the development of the first high-brightness blue LED by Shuji Nakamura in 1994, which led to the first white LED, and eventual creation of the first LED light bulb by Philips in September 2009 (see chapter 5 for further details). Interestingly, this chain of events appears to infer that only the original source of electric lighting emerged due to presumption (based on the notion of electrical power grids that could serve a greater number of applications than gas) whilst most other domestic lighting technologies since have been largely reactive.

2.5.2 Electric vehicles

When the earliest forms of electric vehicles were first demonstrated in the 1830s (see chapter 5), steam engines were very much still at the bleeding edge of transportation technology, with Stephenson's Rocket having only just won the Rainhill trials in 1829 [Perez, 2007]. The progress of steam engine power during this time as a prime mover is outlined in more detail in section 2.5.4. The earliest concepts of using electricity to power vehicles arose when steam-powered locomotives were rapidly advancing, suggesting that the earliest electric vehicles shared the same characteristics as presumptive anomaly. More recently, the reintroduction of electric vehicles after their near extinction in the 1920s follows the development of the first modern hybrid vehicle by GE Research Labs in 1982 (see chapter 5). However, fuel economy improved for internal combustion engine vehicles between 1975 and 1985, as seen in Figs. 2.14 to 2.16 [Zachariadis, 2006].

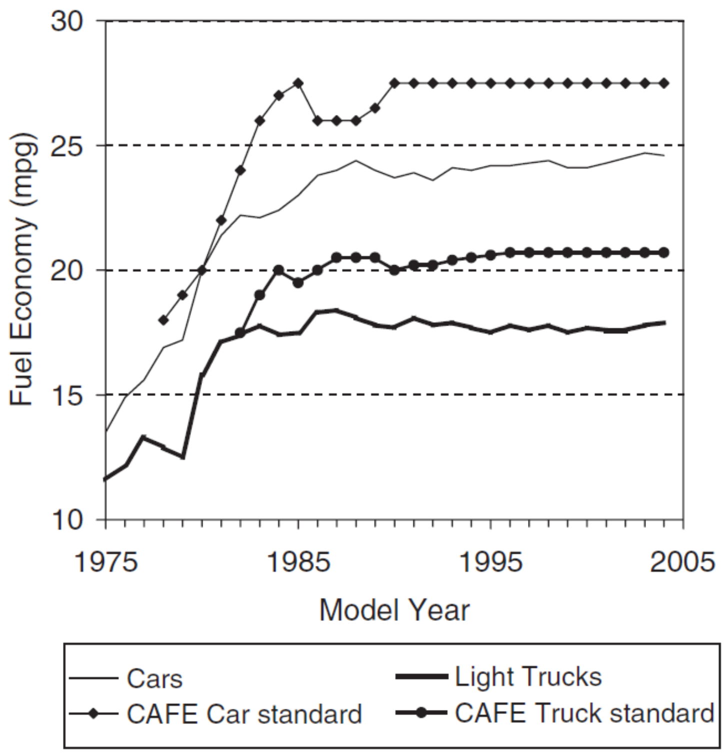


Figure 2.14: Evolution of CAFE standards[1] and sales-weighted average fuel economy of newly registered cars and light trucks in the United States, 1975 - 2004 [Zachariadis, 2006]

[1] The Corporate Average Fuel Economy (CAFE) standards are regulations introduced in the United States in 1975 following the OPEC oil embargo to improve the average fuel economy of cars and light trucks produced for sale in the U.S.

Additionally, Fig. 2.17 indicates that the ratio of fuel consumption to horsepower has continued decreasing (i.e. improving) steadily since 1975 to 2015. Therefore when modern electric cars started being developed seriously in the late 1970s, and adopted again in larger numbers since 2010, this improvement in ICEs was still continuing [Smith, 2014]. However, unlike the original creation of electric vehicles which was inspired in response to the noise and dirt produced by steam carriages [Chan, 2013], the redevelopment of electric vehicles in the 1970s was a reaction to the OPEC oil embargo of 1973. The market shortages and fuel price spikes that ensued brought global oil dependency, depletion of limited fossil resources, and the need for sustainable alternatives to the attention of scientific communities and the wider world [Chan, 2013]. Again, this suggests the reintroduction of electric vehicles was presumptive in nature, rather than reactive.

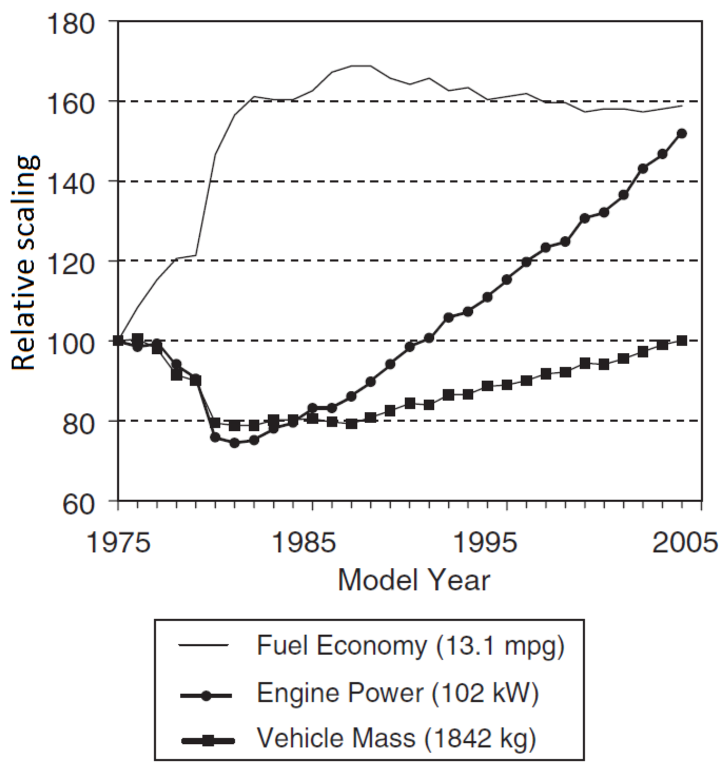


Figure 2.15: Relative evolution (1975 = 100) of sales-weighted average vehicle mass, power output and composite fuel economy of new light duty vehicles in the United States, 1975 - 2004 [Zachariadis, 2006]

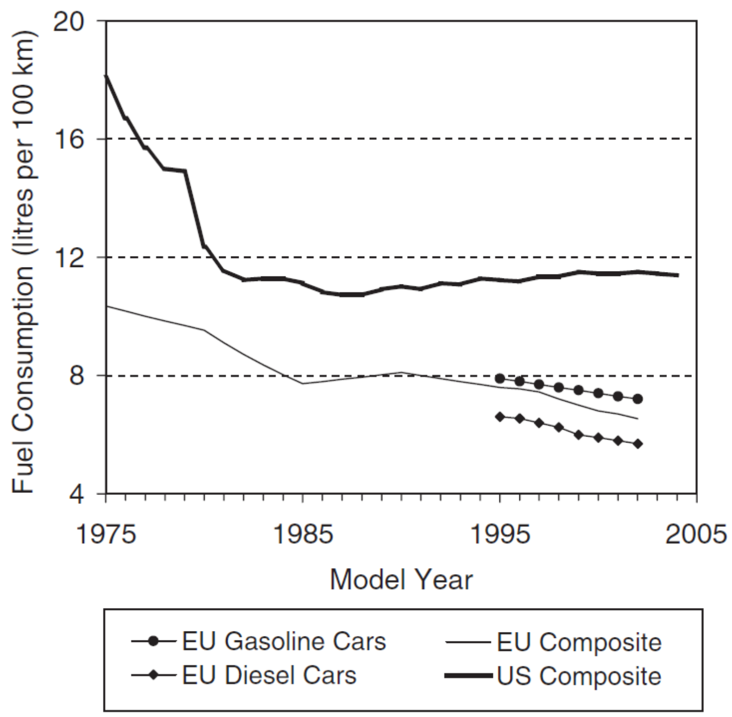


Figure 2.16: Evolution of fuel consumption of new cars in the European Union and the United States, 1975 - 2002 [Zachariadis, 2006]

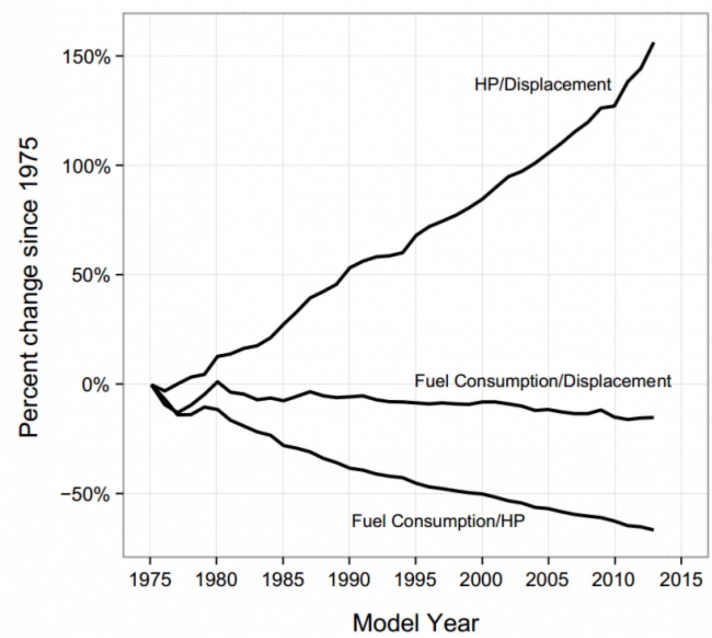


Figure 2.17: Relationships between key vehicle performance metrics since 1975 [Smith, 2014]

2.5.3 Personal printer technologies

Printer resolution and speed are selected as measures of performance here to classify the various personal printer technologies included in Table 2.2. The first type of printer considered, dot matrix, is credited to IBM in 1957 (see chapter 5 and Appendix A). At this time, Teletypes struggled to keep pace with the rapid increases made in computing technologies [Fey and Rivin, 2005]. This was due to the relatively heavy mechanical moving parts within the Teletypes that were a speed restraint to the productivity improvements otherwise expected from computing advances [Fey and Rivin, 2005]. This plateauing in teleprinter speeds from the 1930s to the 1970s is shown in Table 2.3. Consequently, daisy wheel and dot matrix printers were developed in a reactive manner, to enable high-speed printing and graphical outputs in line with more modern computing requirements.

The performance of impact printers was soon outpaced as computing power continued to grow in line with Moore's law, demanding ever faster mechanisms and higher quality images. This can be seen from the stagnation in impact printing speeds between 1982 and 1986 in Fig. 2.18, coupled with the lack of improvement in print resolution between 1978 and 1986 (Fig. 2.19), which allowed both ink jet and laser printers to be commercialised for the mass-market in 1984 (see chapter 5 and Appendix A). During this stalled improvement in print resolution, Canon's original thermal ink jet printer patent was filed in 1979 [Clymer and Asaba, 2008]. The company also introduced the first lower-cost laser printers in the same year, although it was two more years before the first laser printer designed for office use appeared, the Xerox Star 8010. However, the first ink jet printer concept was developed by Siemens in 1951 [MindMachine Associates Limited], whilst laser printers were demonstrated by Xerox in 1969, both of which correspond to the stagnation in Teletypes during this period (see Table 2.3). Additionally, Table 1 in Mayadas et al. [1986] shows that IBM's impact printers maintained a speed of

Table 2.3: Teleprinter speed developments

Year	Speed (Words per minute)	Model	Source
1921	40	Teletype Model 11	[Hallas]
1927	66	Creed Model 3X tape printer	[Smith]
1931	66	Creed Model 7 teleprinter	[Smith]
1934	140	Creed Model 7P offline keyboard perforator	[Smith]
1950	100	Teletype Model 28 (first military use)	[Hallas]
1953	100	Teletype Model 28 (general public)	[Hallas]
1958	100	Creed Model 75 teleprinter	[Smith]
1963	100	Teletype Model 33	[Pollard]
1974	133	Creed Model 2300 semi-electronic teleprinter	[Smith]

around 1,000 lines per minute from 1955 until the introduction of the IBM 3211 in 1970. Therefore it can be assumed that both thermal ink jet and laser printers arose due to the perceived functional-failure of either Teletypes or dot matrix printers. In the meantime, ideas surrounding thermal printing also first appeared in the 1950s [H. Epstein and T. R. R, 1959] as a way of improving speed relative to existing impact printing techniques before being demonstrated by Gerber Scientific plotters in the 1960s, although it was not until around 1972 that direct thermal printing became a commercial reality. As such, the initial demonstration of this technology corresponds to the stagnation in Teletype and dot matrix printer speeds from the late 1950s through the 1960s.

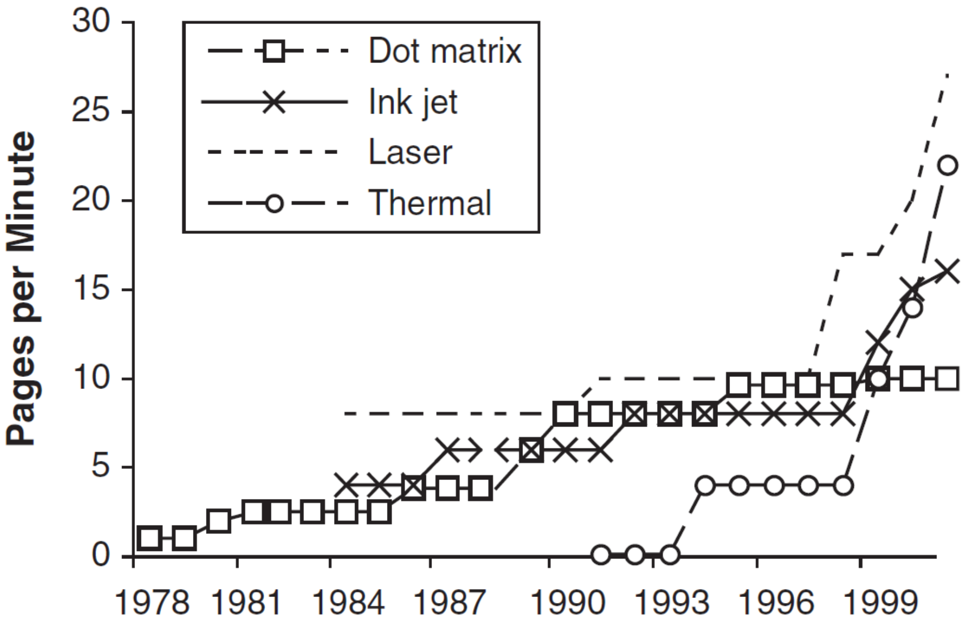


Figure 2.18: Evolution of printer speeds by technology [Sood and Tellis, 2005]

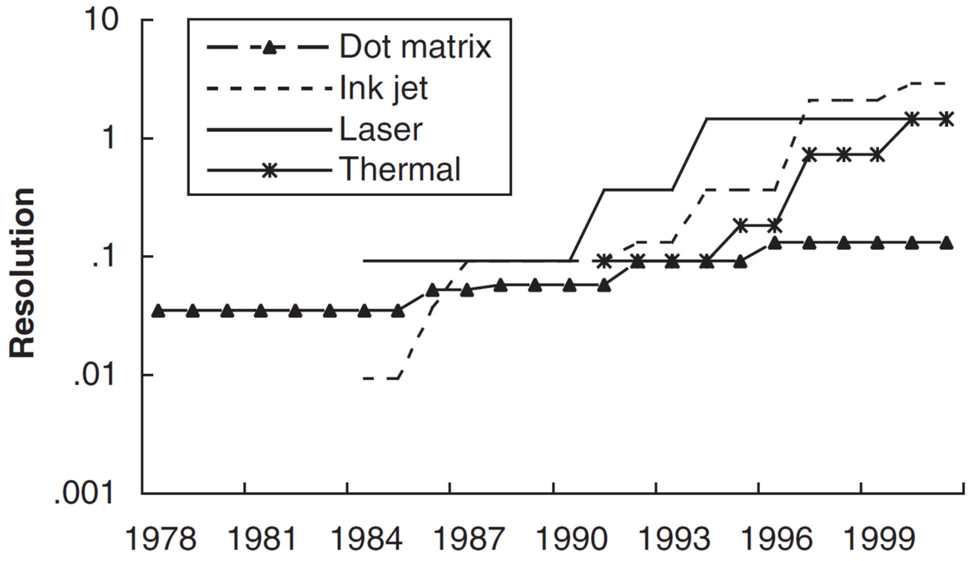


Figure 2.19: Evolution of printer resolutions by technology [Sood and Tellis, 2005]

2.5.4 Renewable and nuclear electricity generation sources

The *Heat Rate* (i.e. power plant efficiency) measure of performance is primarily used here to classify the various renewable and nuclear electricity generation technologies in Table 2.2. This metric is used to demonstrate the continued performance improvements in fossil fuel technologies throughout the majority of the twentieth century. Fig. 2.20 to Fig. 2.26 illustrate steady improvements in:

1. coal and gas heat rates in the U.S. between 1950 and 1960, and again a steady improvement in gas heat rates between approximately 1987 and 2007 (Fig. 2.20 [National Petroleum Council, 2007]).
2. thermal power plant heat rates in China, Japan, and the U.S. between 1980 and 2002 (Fig. 2.21 [National Petroleum Council, 2007]).
3. coal-fired heat rates and power plant efficiency between approximately 1965 and 1990 in Japan, Australia, Germany, Poland, Italy, and the UK (amongst others) (Fig. 2.22 [Coal Industry Advisory Board, 2010]).
4. coal-fired heat rates of Siemens steam turbine plants between 1973 and 2000 (Fig. 2.23 [Schaarschmidt et al., 2005]).
5. Elsam's coal-fired power plants between 1950 and 2003 (Fig. 2.24 [Graus and Worrell, 2009]).
6. average energy efficiency in coal and gas power plants in EU27 countries between 1990 and 2005 (Fig. 2.25 [Graus and Worrell, 2009]).
7. gas-fired heat rates in California between 2001 and 2010 (Fig. 2.26 [Nyberg, 2013]).

From this, it is evident that efficiency improvements in existing fossil fuel technologies materialised globally during the second half of the twentieth century, spanning nearly continuously from 1950 until 2010.

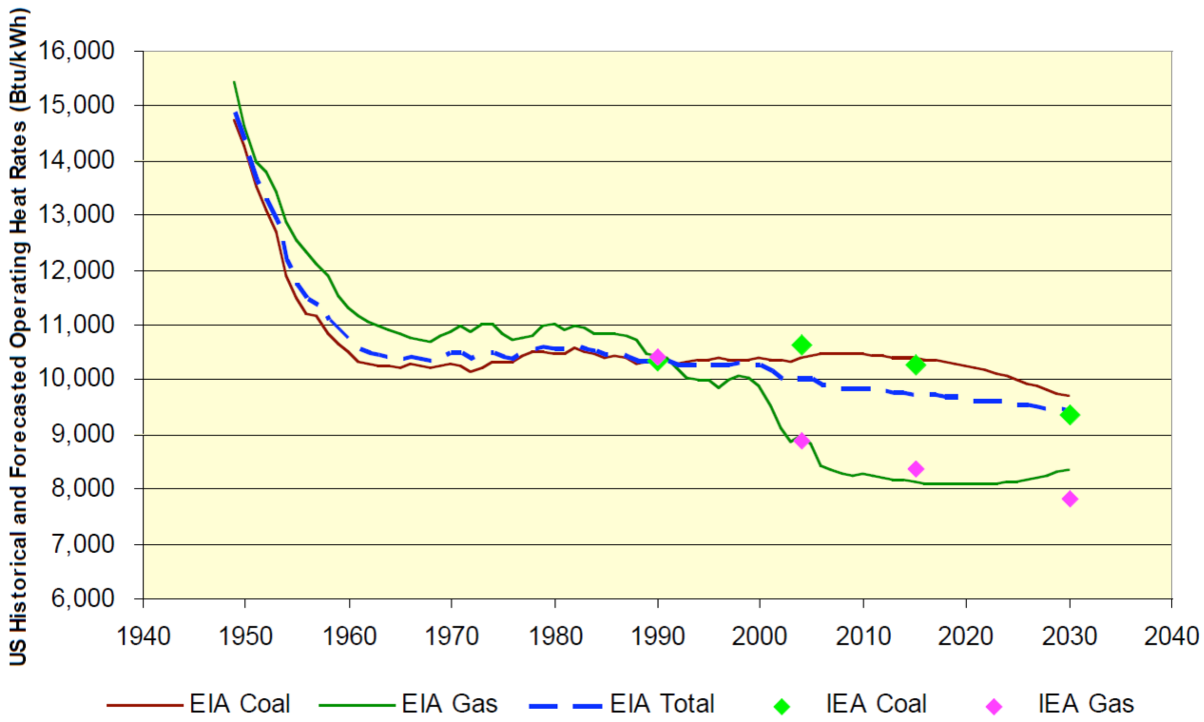


Figure 2.20: U.S. historical and forecast heat rates from EIA and IEA data [National Petroleum Council, 2007]

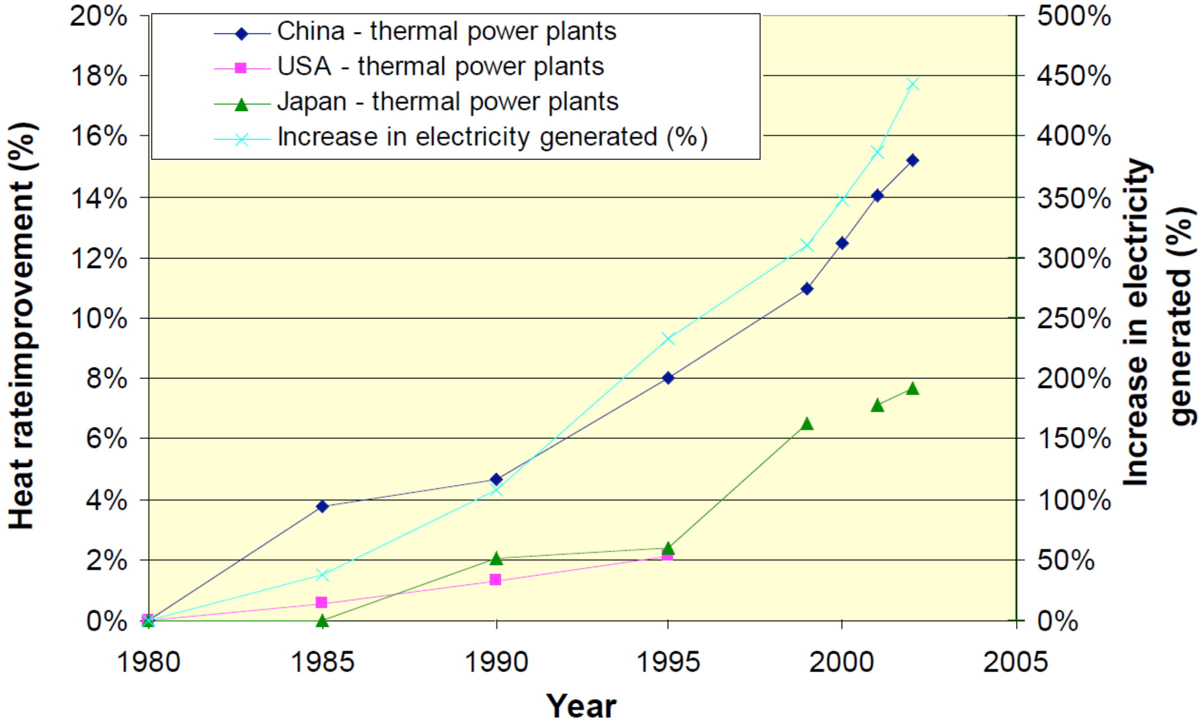
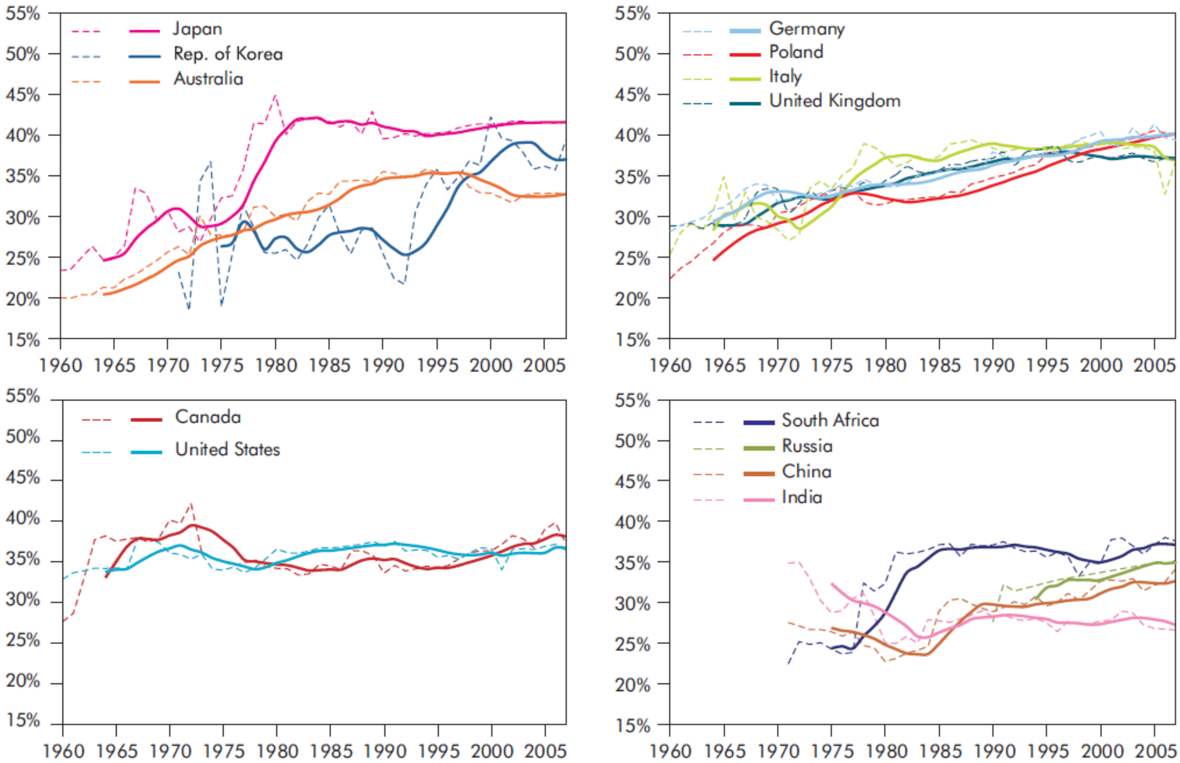


Figure 2.21: Historical efficiency improvements in thermal power plants [National Petroleum Council, 2007]



Notes: Annual data are shown with dashed lines, five-year moving averages with solid lines. For Russia, data are shown for 1990-1992, 1996 and 2005-2007. Data for the intervening years show inexplicable efficiency improvements and may need revising.

Figure 2.22: Evolution of coal-fired heat and power plant efficiency around the world, 1960 - 2007 [Coal Industry Advisory Board, 2010]

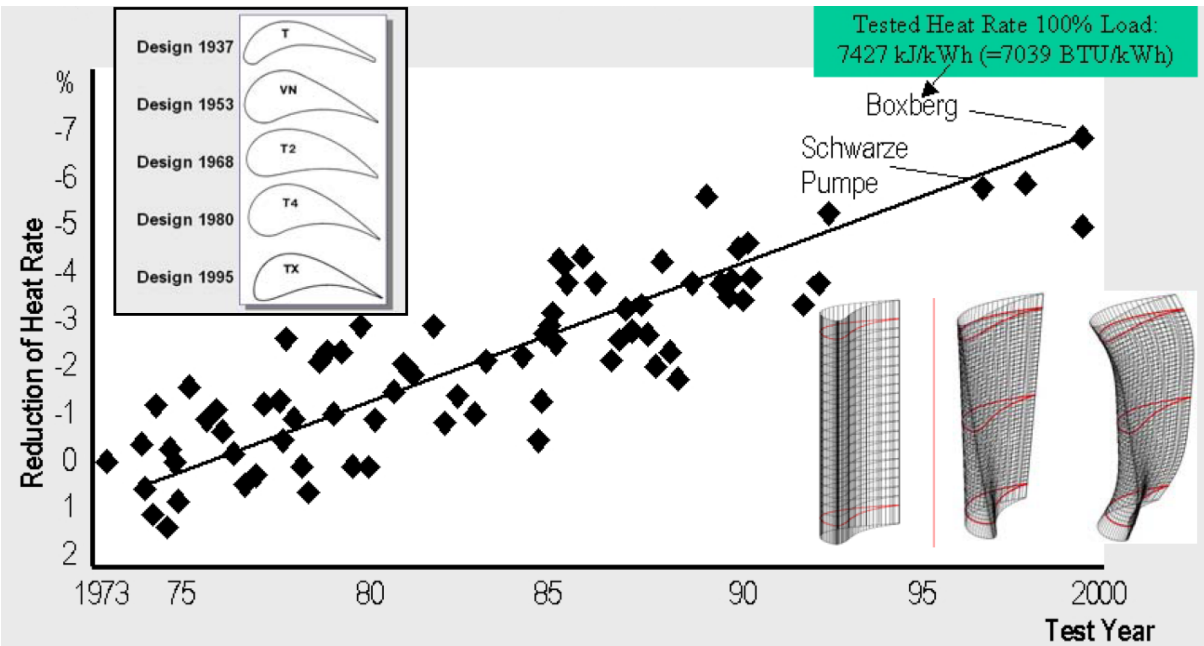


Figure 2.23: Trend of heat rate development at Siemens steam turbine plants, 1973 - 2000 [Schaarschmidt et al., 2005]

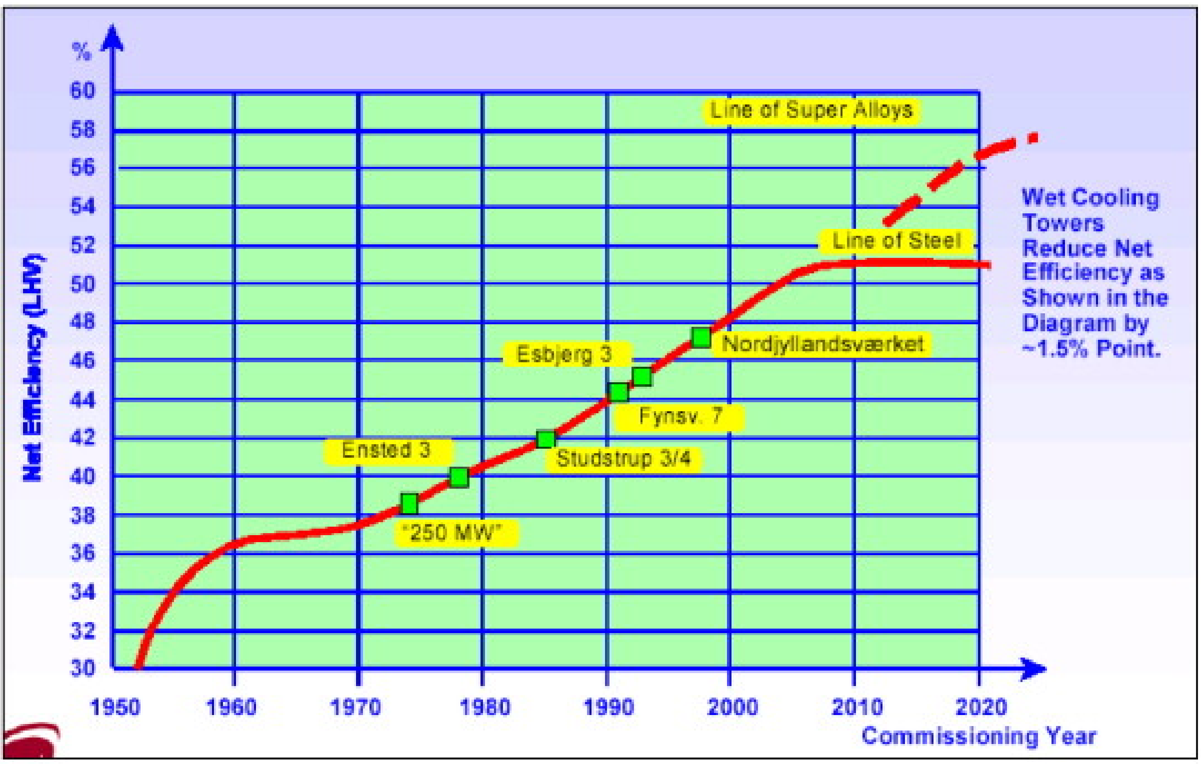


Figure 2.24: Past and projected future development in efficiency of Elsam's coal-fired power plants [Graus and Worrell, 2009]

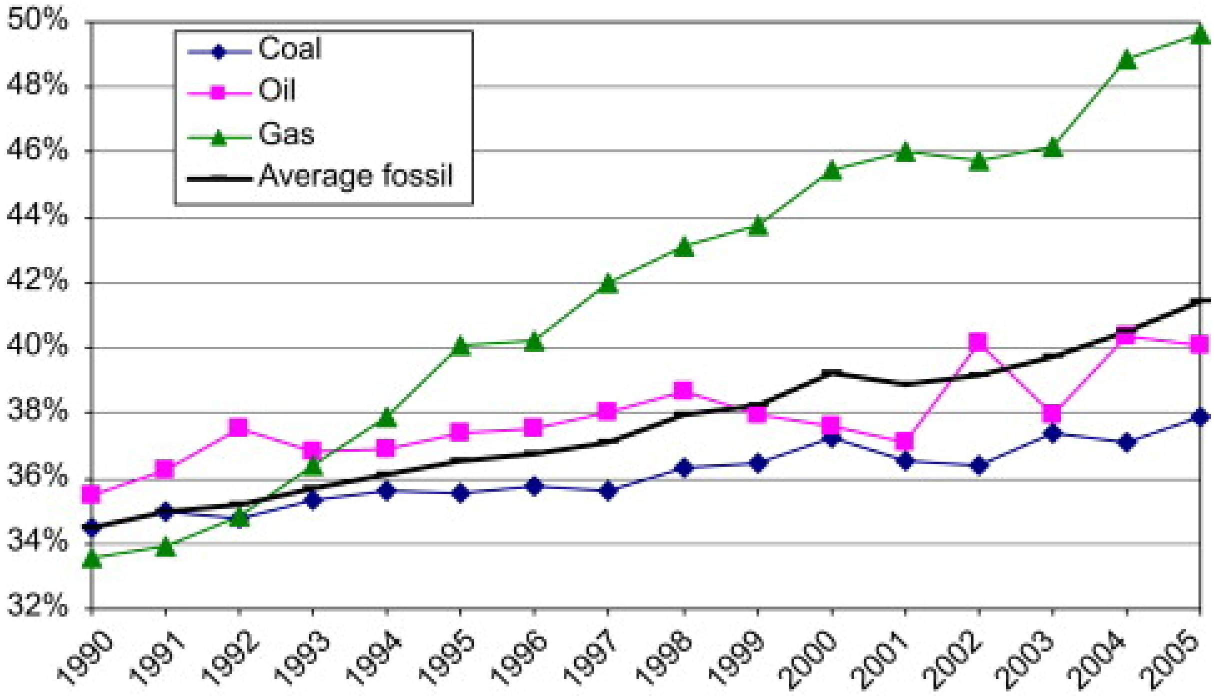


Figure 2.25: Average energy efficiency per fuel source in the EU, based on IEA data [Graus and Worrell, 2009]

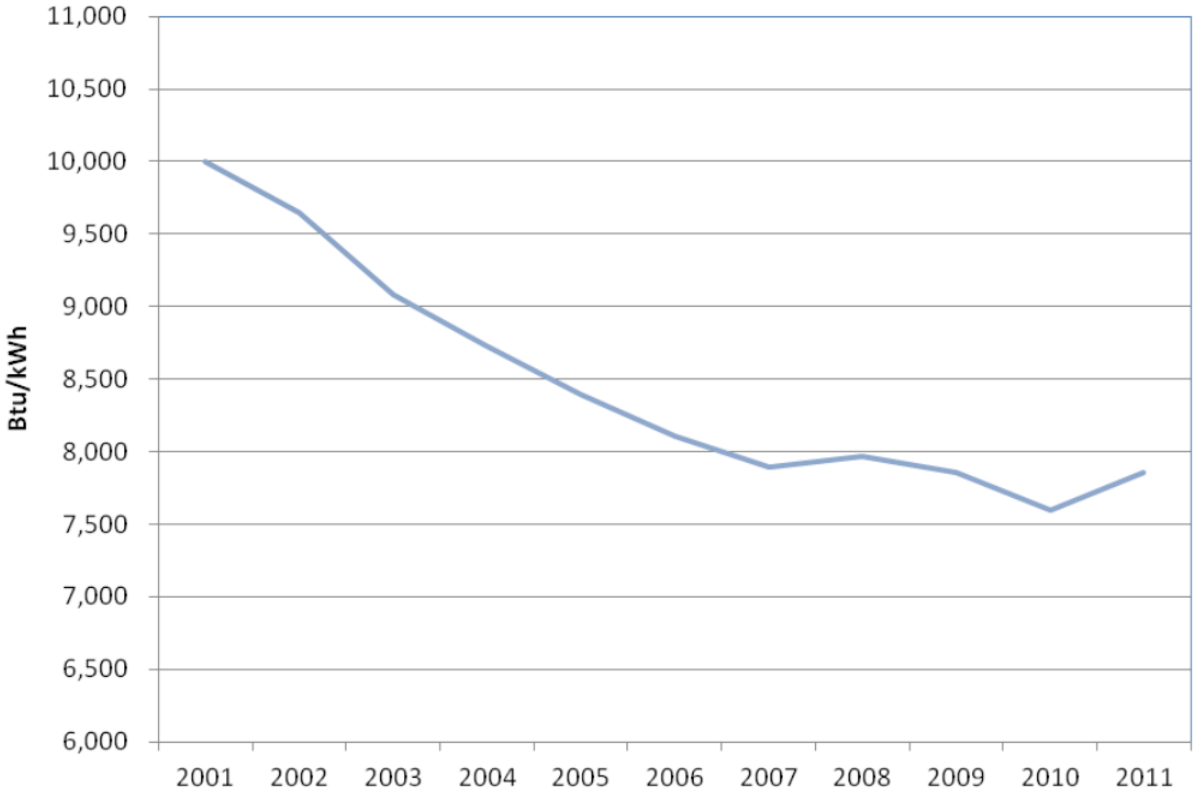


Figure 2.26: Gas-fired heat rates for electricity generation in California [Nyberg, 2013]

For examining biomass and fossil fuel performance trends prior to 1950, power plant efficiency data is not readily available (or in some cases existing). *Heat rate* is subsequently replaced by the *power of the largest prime mover* as the performance measure of functionality, as in Fig. 2.27 [Smil, 2004]. From this, it is evident that steam engines advanced steadily between approximately 1700 and 1850, before being overtaken in terms of performance by water turbines between approximately 1850 and 1900, which in turn were supplanted by steam turbines around 1900 [Smil, 2004].

Considering next the emergence of renewable energy sources, these have largely arisen throughout the nineteenth and twentieth centuries. However, for many (but not all) of the renewable energy supplies considered, these technologies were commercially unsuccessful in their earliest incarnations, and the majority would have to wait until renewed interest in the 1970s enabled them to be re-evaluated (brought on by high oil prices [Smil, 2004, Chan, 2013]). Subsequent re-examination of these technologies and global dependencies on oil supplies led to greater awareness of the climate change implications of fossil fuels. Ensuing studies followed that highlighted the environmental damage of CO_2 and greenhouse gas emissions, effectively identifying physical limits associated with continued fossil fuel usage. This means that in most cases the resurgence of renewable technologies in the second half of the 20th century, which occurred in parallel to continued fossil fuel developments, was driven by considerations of foreseeable energy supply and climate change constraints. This implies that the re-emergence of these technologies could be considered to be presumptive in nature. However, these later environmental and supply factors were not generally of concern at the time of original inception.

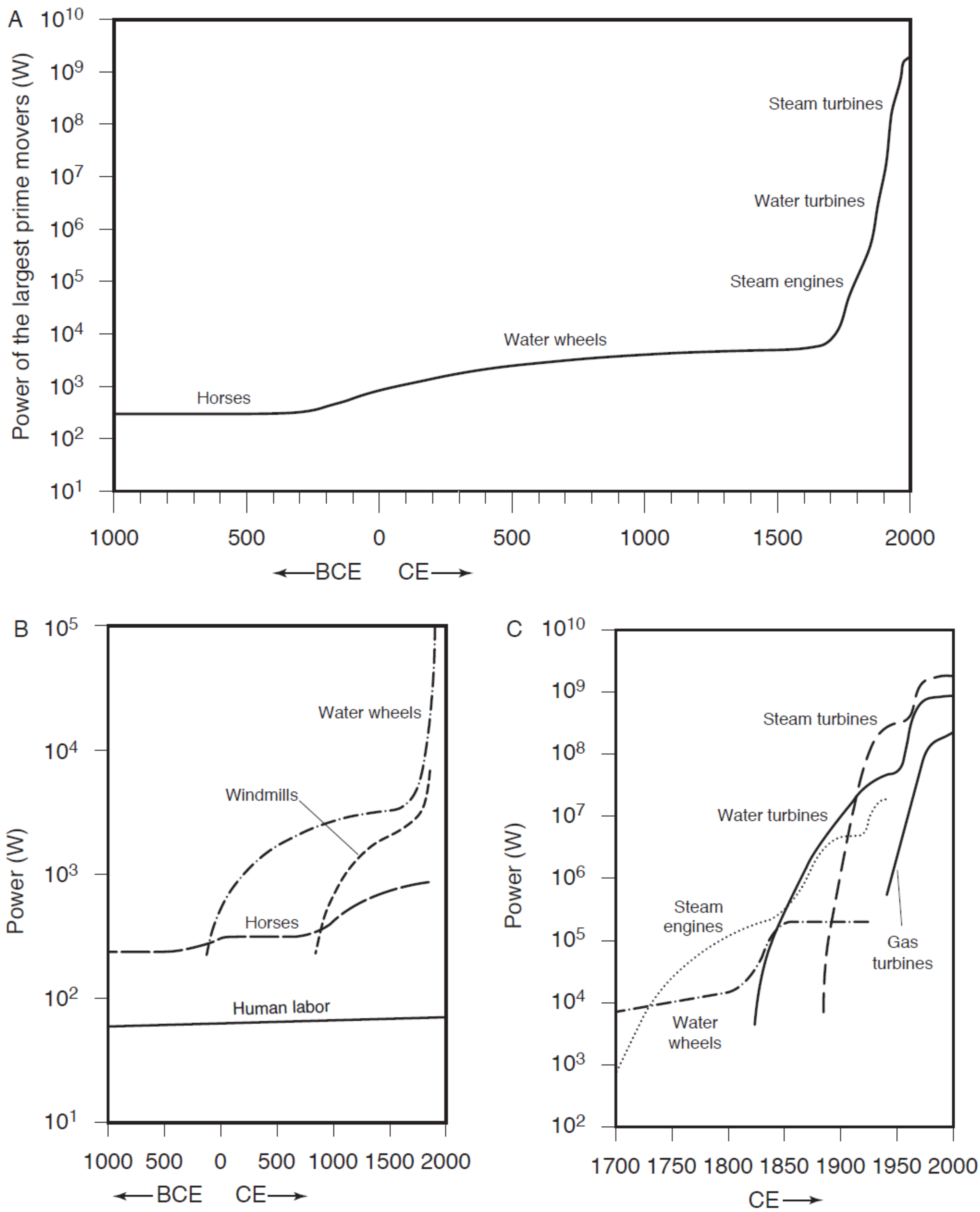


Figure 2.27: The maximum power of prime movers shown as the sequence of the highest capacity converters for the span of the past 3000 years (A) and shown in detail for the periods 1000BCE to 1700CE and 1700CE to 2000CE (B and C) [Smil, 2004]

The earliest renewable energy developments considered in this study were based on tide, wave, and ocean based electricity generation, and first appeared in a patent in 1799 by Girard and son [Tester et al., 2012] where it was proposed that energy could be extracted from ocean waves. Steam engines were still undergoing considerable development in terms of power output at the end of the 18th century (see [Smil, 2004] and Fig. 2.27), although this was increasing primarily due to larger and larger steam engines rather than improvements in conversion efficiency. Efficiency improvements at this time were limited by manufacturing methods, mechanical ability, and the lack of machine tools [Roe, 1916]). The insight for marine energy came therefore from combining the notion of practically unlimited kinetic energy from waves with the knowledge that water wheels were a primary source of motive power prior to the introduction of steam engines [Ross, 2012]. In this regard, the original concept of wave power appears to be more symptomatic of a presumptive technology than a reactive one if considering the spatial implications at the time for continually increasing power output. More modern scientific wave energy efforts were pioneered by Yoshio Masuda's experiments in the 1940s and proposed articulated raft in the 1950s. This was followed by the Rance Tidal Power Station in France, the world's first large-scale tidal power plant, which began operation in 1966. Consequently, more recent marine power efforts also appear to have emerged at a time when existing fossil fuel technologies were still advancing, as seen in Fig. 2.20 and Fig. 2.24.

The next form of renewable electricity generation to appear, hydropower, traces its origins to the mathematically inspired development of the reaction water turbine by Benoit Fourneyron in 1832 [Smil, 2004]. Between 1800 and 1850, the power output of steam engines was nevertheless increasing (see Fig. 2.27). In parallel, the maximum power output of water wheels had been calculated for the first time as being physically limited to about 60% for over shot wheels by John Smeaton in 1759 [Müller, 2004]. However, Fourneyron's demonstration of an 80% efficient turbine in 1837 hinted at possibilities of even greater increases in power output beyond those that steam engines or water wheels, with their poorer expected conversion efficiency limits, could hope to offer [Smil, 2004, Price, 2005]. As such, water turbine and subsequent hydro mechanical and hydroelectric developments also appear to have followed a presumptive leap based on similar notions to those that drove the earliest marine power developments.

In terms of wind energy generation, the first windmill used to produce electric power was built in July 1887 by Professor James Blyth in Scotland. Again, Fig. 2.27 shows that at this time, water turbines and steam engines were both still improving, although more convincingly in the case of water turbines. However, based on his own insights into the relatively new technologies of electricity and magnetism, Blyth foresaw increased future use of electricity for industrial and lighting applications, whilst questioning the convenience of hydro power as a means of generation [Price, 2005]. More recent developments in wind energy following the oil crisis in 1973, and the introduction of Feed-In Tariffs for wind power in California in 1983 have subsequently progressed whilst other fossil fuel developments have occurred in the second half of the twentieth century.

By the time solar photovoltaics (PV) were conceived by Charles Fritts in the 1880s, water turbines had taken over as the most promising prime mover, although it was not until 1931 that Bruno Lange developed the first photo cell using silver selenide instead of copper oxide. Fig. 2.27 again shows that in the 1880s, water turbines and steam engines were both increasing steadily in power output, whilst in the 1930s steam turbines overtook water turbines in leading progress in electricity generation technology. At the time of his invention, Charles Fritts (supported by Werner von Siemens [Siemens, 1885]) saw an opportunity to compete against Thomas Edison's early coal-fired power plants [Chodos, 2009], based on expectations of unlimited solar energy that would ultimately lead to cost-free electricity generation [Siemens, 1885]. In 1954, when the first silicon solar cell was created by Gerald Pearson, Calvin Fuller, and Daryl Chapin, coal power plants were still seeing notable improvements, as noted previously (see Fig. 2.20 and Fig. 2.24). As such, solar PV is once more typical of a less reactionary technology substitution.

The same can be said for geothermal, nuclear, and solar thermal electricity generation, which were first demonstrated in 1904, 1951, and 1968 respectively with similar expectations of cheap and unlimited supplies of energy. These dates correspond to 1) the testing of the first geothermal plant in Larderello; 2) the first generation of electricity from the EBR-1 experimental Nuclear reactor in Arco, Idaho (followed by the first supply to a national grid system from the USSR's Obninsk power plant in 1954); and 3) the first concentrated-solar power plant created by Professor Giovanni Francia in Sant'Ilario, Italy. Subsequently, most renewable energy formats began being seriously adopted between 1990 and 2010, but can be seen to emerge from scientific insights much earlier.

2.5.5 Thin-film-transistor liquid-crystal displays (TFT-LCD)

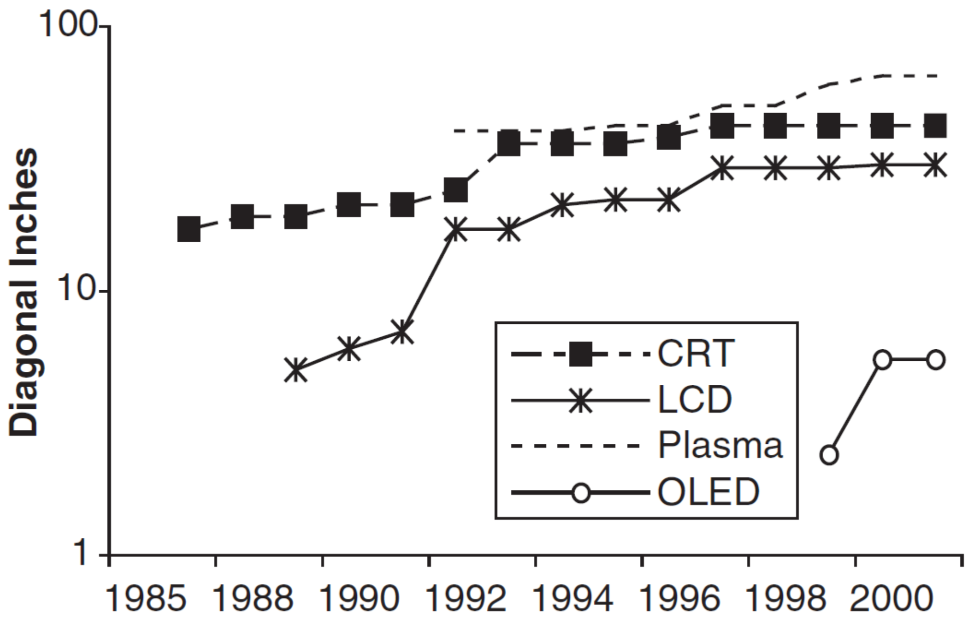


Figure 2.28: Evolution of screen size by display monitor technology [Sood and Tellis, 2005]

Both monitor depth and screen size are commonly used performance metrics for the evolution of display screen technologies (amongst others including colour intensity, and power consumption). Monitor depth played a significant role in the development of LCDs, as various attempts had historically tried, and failed, to squeeze the traditional 3D Cathode Ray Tube (CRT) into two dimensions, or to at least substantially reduce the depth. The invention of LCDs in 1964 made flat-screen displays possible, which at the time were beyond the manufacturability of CRT developers due to mechanical complexity (additional details on TFT-LCD development are provided in chapter 5 and Appendix A). Consequently, LCDs arose partially due to the stagnation in CRT monitor depth [Mentley, 2002]. CRTs were originally limited to a maximum diagonal screen size of about 38" (which later rose to about 45"), whilst LCD screens can now be above 100". However, the depth required for larger CRT screens made the biggest CRT TVs unwieldy and very heavy. Fig. 2.28 illustrates that CRT screen sizes remained largely static from 1985 to 1990, when the first practical LCD TVs started to appear (Sharp introduced a 3-inch pocket TV in 1986, followed by a 3-inch colour pocket TV in 1987, and an announcement to develop a 14-inch colour TFT-LCD display in 1988 [Ishii, 2007]). These events would therefore suggest that TFT-LCDs emerged as a reaction to existing constraints encountered for CRT screens.

2.5.6 Turbojets and jet propulsion

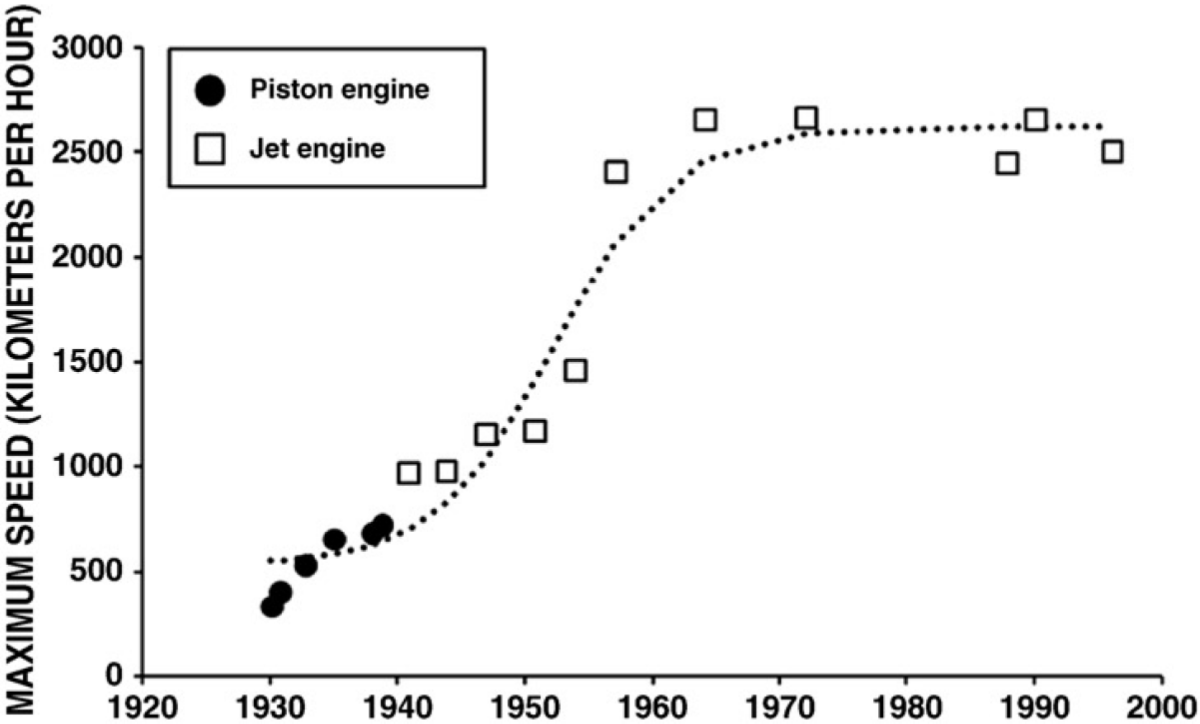


Figure 2.29: Evolution of maximum speed of military fighter aircraft by technology [Chang and Baek, 2010]

One of the key performance metrics for any mode of transport is the maximum vehicle speed. The transition from piston to jet engines in aviation followed a relatively smooth maximum speed transition (see Fig. 2.29), implying that the need to shift to the next technology was anticipated some time before piston engines actually reached the limits of their design. This agrees with the observations made by Edward Constant [Constant, 1973] (see section 2.2), where he notes that Frank Whittle's gas turbine patent registered in 1930 was approximately a decade ahead of piston engines reaching their eventual top speed of around 750 km/h. This was driven by recognition of limitations imposed by propeller compressibility effects at higher speeds, and that to maintain the current performance trajectory a shift to turbomachinery would be required. In addition, if considering demands from more general power generation applications outside of aerospace, Fig. 2.27 shows that gas turbine development in the 1930s and 1940s began whilst the maximum power output of water and steam turbines was still improving. Although gas turbine development built on knowledge acquired directly from the development of steam turbines, the move to develop a new form of prime mover at this time was informed by advances in aero and thermodynamics, and the desire for smaller, lighter weight, propulsion systems for aircraft. As such, the transitions observed in aerospace, and later in power generation, do not appear to be a result of any observed technological (i.e. functional) failure, making the claim of presumptive anomaly reasonable.

2.5.7 Telecommunication technologies

Bandwidth, measured in 'Bits per second', provides a suitable performance metric for assessing telecommunication and data transfer technologies. The earliest telecommunication technology considered in this study is fixed (or *landline*) telephone systems, which were first patented by Alexander Graham Bell in 1876 (see chapter 5), yet attained nearly 50,000 adopters by 1880 [Gabel, 1969]. At this time, telegraph technologies were still undergoing rapid development, as shown in Fig. 2.30 [Chang and Baek, 2010]. This shows the bandwidth of single cable technologies, used in telegraphy, growing significantly from 1858 to 1880 (this relates specifically to telegraph lines in Table A2 in Koh and Magee [2006]), indicating that the emergence of the telephone was more likely to be based on presumptive insights. More specifically, the inspiration behind transmitting voice signals by electricity over wires can be traced to earlier mechanical acoustic devices (such as the tin can telephone, or *'lover's phone'* where sound is transmitted by mechanical vibrations along a taut string from one diaphragm to another), coupled with the demonstration of electromagnetic transmission of telegraphic signals in the 1830s and 1840s [Hooke, 1705, Beauchamp, 2001].

As both telegraph and telephone networks expanded rapidly in the 19th century, deep sea links began to appear between nations to provide continental and eventually global communication links. These were initially based on single cable lines laid on the sea beds. Coaxial cables led to a significant leap in technical performance when introduced into the undersea cable network in the 1950s (evident from the bandwidth jump in Fig. 2.30), although improvements in cost performance were greatly hampered by the telecommunications monopoly that extended from the 1960s to 1995 [Roberts, 2000]. During this time, the cost performance for leased lines to make a cross-country packet network only halved every 79 months [Roberts, 2000]. In parallel, there was a rapid decrease in the cost of computing which made it economically viable to add computing to a communications network using packet switching. In this sense, an opportunity arose for computing technologies to reduce the cost (and in turn increase the speed) of information transfer and communication networks beyond the now largely stagnant developments in voice traffic. This was achieved through the development of the ARPANET in 1969, the precursor of the modern day internet. The stagnation in voice communication methods can be seen in Fig. 2.31, where 'Voice traffic' bits per second level remains largely unchanged between 1970 and 2010. Internet technologies continued improving, transitioning to the TCP/IP framework (i.e. the modern-day internet) in 1983, before overtaking voice technologies for information transfer around 2000.

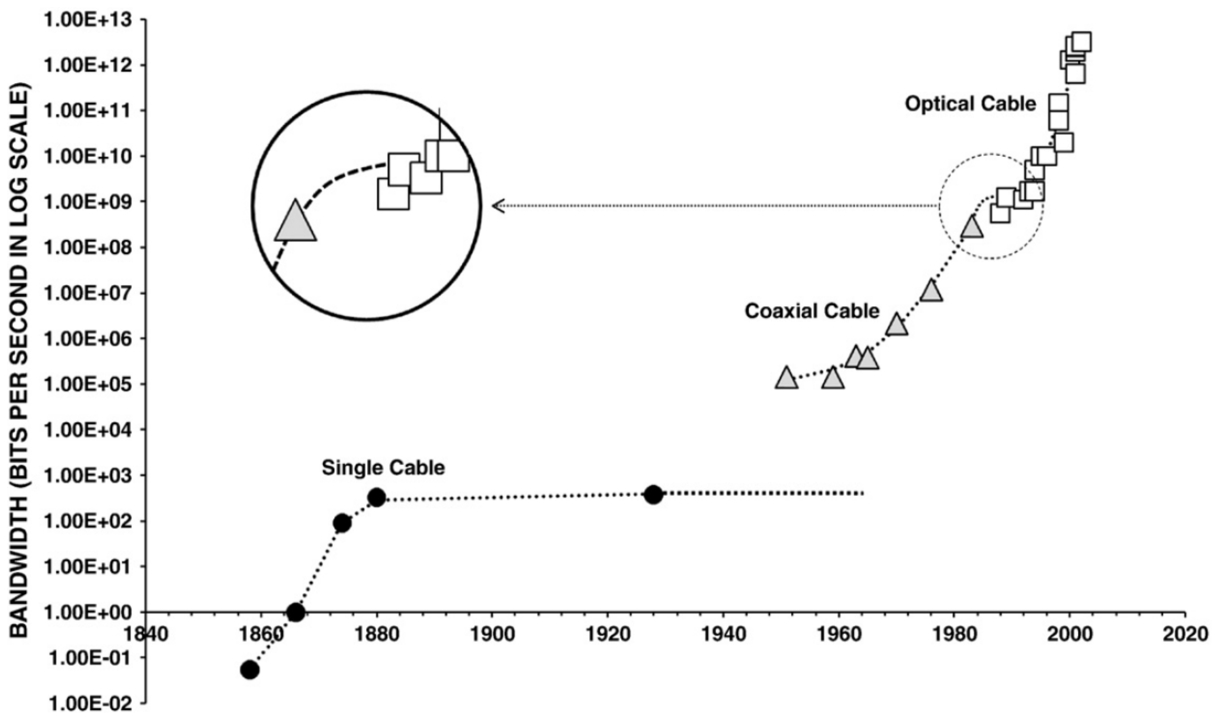


Figure 2.30: Bandwidth evolution of undersea cable technologies [Chang and Baek, 2010]

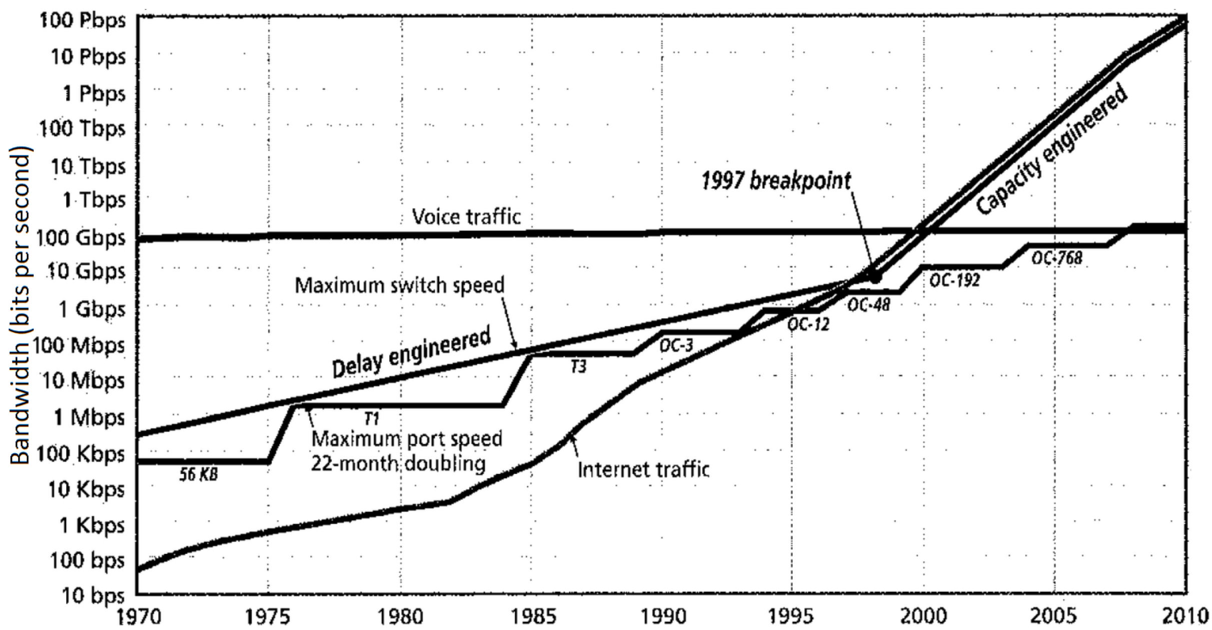


Figure 2.31: Growth trends of internet traffic, voice traffic, maximum trunk speed, and maximum switch speed required for large cities [Roberts, 2000]

Around the same time, increases in the bandwidth of copper and aluminium wires stagnated between approximately 1965 and 1984 (i.e. a temporary functional failure), as shown in Fig. 2.32 [Sood and Tellis, 2005]. This stagnation in bandwidth was driven by the distance and high frequency signal limitations encountered for copper and aluminium wires, that meant fibre optics offered much greater potential for high-volume, long distance, traffic. During this period, Charles Kao and George Hockham developed the basis for fibre optic communications in 1965/66 (see chapter 5), leading to the development of the first optics by Corning Glass Works in 1970.

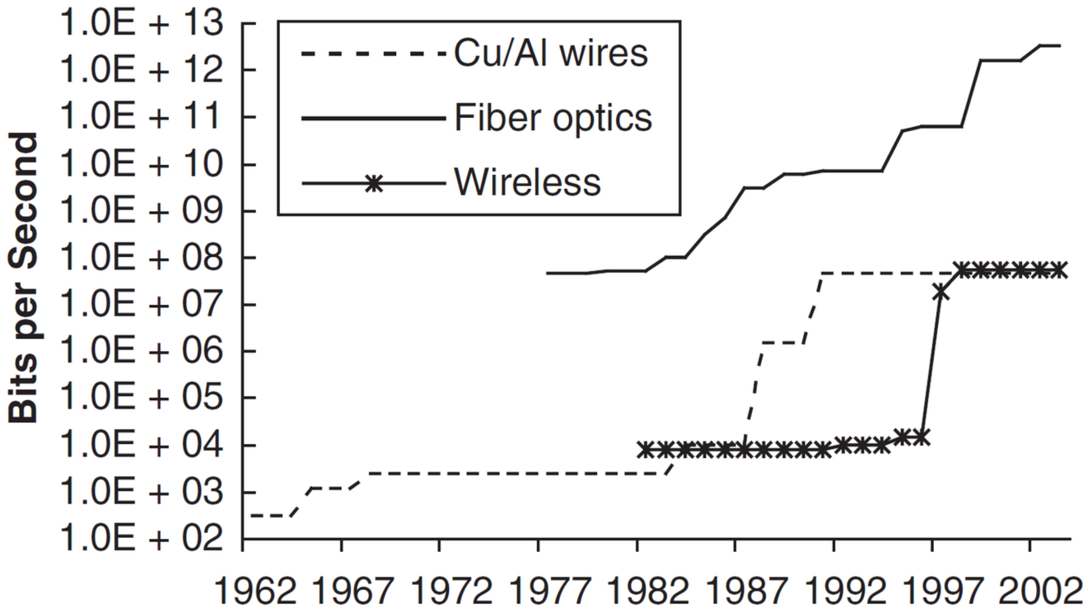


Figure 2.32: Bandwidth evolution in data transfer technologies [Sood and Tellis, 2005]

However, when considering fibre optics in terms of undersea cable technologies, the bandwidth (bits per second) measure of performance for coaxial cable systems was potentially increasing in 1988 when optical cables were introduced (see Fig. 2.30), and was still increasing in 1978 when AT&T, the British Post Office, and Standard Telephones and Cables committed to developing a single-mode transatlantic fibre cable [Chang and Baek, 2010]. This would suggest that the move to fibre optic cables in undersea cable technologies was due to presumptive anomaly as opposed to technological failure. This was potentially guided by the existing transition to fibre optic cables for data transfer following the stagnation of copper and aluminium wires observed between approximately 1965 and 1984.

Following close behind breakthroughs in fibre optics, wireless data transfer technologies were first developed at the University of Hawaii in 1971 (see chapter 5). This emerges in parallel to fibre optics during the stalled development of copper and aluminium cables for use in data transfer. Subsequently, wireless data transfer entered the mass-market when frequencies for mobile networks became available in the early 1980s, with frequencies suitable for Wi-Fi allocated for commercial use in the U.S. in 1985.

2.5.8 Non-starter technologies

In addition to the broader modes of substitution outlined in Table 2.2, other technologies have been identified as *non-starters*; these are marginalised technologies that were never mass commercialised. In many cases these technologies could have been adapted for the target markets considered, but were either never used or failed to demonstrate the required features or performance and cost improvements necessary to warrant further development beyond initial trials. Examples of non-starter technologies include wire recorders as an alternative to magnetic tape technology, and chain printers as an alternative to dot matrix printers [Sood and Tellis, 2005]. Wire recorders failed to take-off after they were excluded from the standard-setting process in favour of magnetic tape technology, leading to "technological lock-out", whilst early chain printers were quickly eclipsed by the superior performance of the dot matrix design [Sood and Tellis, 2005]. Non-starters are excluded in this study as there is often very little patent data pertaining to these technologies due to their very brief life-spans. However, as this study is based on technologies that are known to have been successfully commercialised (falling into either reactive or presumptive categories) it is not believed their inclusion would influence the results presented here. In reality, non-starters would need to be included for predicting the commercial success or failure of emerging technologies in the first instance [Sood and Tellis, 2005], but this additional classifier dimension is left as an extension for future studies.

2.6 Measuring perceptions of limits of science and technology

To determine the likely mode of substitution, Constant's discussion of technological anomalies, outlined in section 2.2, implies that a relative understanding of the development efforts associated with both science and technology is required. On this subject, many indicators of scientific and technological progress have been developed in the fields of bibliometrics and scientometrics in recent decades. Whilst largely developed for the purposes of identifying and targeting gaps in existing knowledge, and determining the effectiveness of funding in specific fields of research, these indicators also provide a systematic approach to compare development trends across a broad range of scientific domains. When attempting to measure science and technological extension opportunities, it is important to ensure that any measurements taken are suitable indicators of the development characteristics that are being studied. In this regard, conceptual distinctions exist between scientific activity, scientific production, and scientific progress [Martin, 1996]:

1. **Scientific activity:** consumption of the inputs to basic research (e.g. related to the number of scientists involved, as well as levels of funding, support staff and equipment)
2. **Scientific production:** extent to which consumption of resources creates a body of scientific results. Results are embodied both in research publications and in other types of less formal communication between scientists
3. **Scientific progress:** extent to which scientific activity results in substantive contributions to scientific knowledge

Based on this, indicators of scientific progress, such as citation analysis, are normally considered most appropriate for assessing scientists' success in producing new scientific knowledge and for identifying emerging areas of development, leading to their common usage in tenure review processes [Narin and Hamilton, 1996]. Publication counts meanwhile, are considered to provide a reasonable measure of scientific production, but are thought to be much less adequate as an indicator of contributions to scientific progress due to the unclear value of each publication's individual contribution to knowledge. Publication counts actually reflect both the level of scientific progress made by individuals or groups and additional factors relating to the social and political pressures behind a study (e.g. publication practices of the employing institution, country and research area, or emphasis placed on publications for obtaining promotion or grants) [Verbeek et al., 2002, Martin, 1996]. Realistically, these other extraneous factors cannot be assumed to be small in comparison to the scientific claims made, or randomly distributed so as to cancel each other out [Martin, 1996]. However, in this study the emphasis is not on assessing the performance or influence on technical direction of a specific set of papers, but rather to gauge adoption trends of the field as a whole. As technology diffusion models also rely on non-invested parties being made aware of scientific and technological progress, communication and promotion of scientific research are important factors to include in adoption processes [Bass, 2004]. Adoption is equally dependent on perceptions of current scientific and technological rates of progress (shaped by social and political pressures, as well as technical [Gooday, 1998, Edgerton, 2011]), rather than the actual rates of progress (shaped by technical contributions to knowledge). Lastly, diffusion effects are population size, word-of-mouth, and time dependent [Bass, 2004]. Technology adoption specific considerations are discussed in further detail in section 2.7. Accordingly, measures of scientific production are felt to be a more relevant indication of likelihood to adopt than pure measures of scientific progress, although they could also indicate potentially contentious or controversial topics that generate lots of different opinions. However, controversy does not necessarily prevent adoption, and in some cases, may accelerate substitution mechanisms [Hall and Rosson, 2006]. Consequently, for the purposes of this study, the scientific production associated with debate over contentious or controversial technologies is not believed to significantly skew the trends presented here in either direction away from the intended simplified reflection of real-world adoption characteristics.

Besides the interpretation of commonly used bibliometric measures and relative significance to measuring scientific developments, it is important to consider best practice in obtaining these measures. In this regard, the World Intellectual Property Organisation (WIPO) has published a set of guidelines relating to producing patent landscaping reports [Trippe, 2015]. This suggests that a patent search strategy that enables a 90% recall rate for search results, whilst maintaining a 70% threshold for precision, will be sufficient to reduce the likelihood of finding statistically relevant items appearing in subsequent analysis steps that are significantly off-topic [Trippe, 2015]. The WIPO guidelines note that off-topic records are not normally associated with major trends, meaning they typically are not ‘seen’ by the analysis, although any statistical findings should still be validated [Trippe, 2015].

2.7 Modelling of technology diffusion and adoption

Having considered the characteristics of technological substitutions and influences of scientific and technological development, this chapter now turns its attention to the modelling and forecasting of technology adoption. The preceding sections have highlighted the socio-technical nature of technology adoption, and consequently models of technology diffusion are dependent on a range of both technical and human-centric measures. Economic parameters including GDP, disposable income levels, and labour costs may be considered in projections of new technologies, along with less tangible social drivers that encourage populations to adopt, such as consumer confidence. Similarities can also be seen between diffusivity studies and complex adaptive systems (CAS) in terms of their mathematical complexity (need for computer simulation), asymmetric and irreversible path in time (the inability to return to initial starting conditions by re-winding the system), and nondeterministic nature [Rogers et al., 2005]. Whereas a bottom-up approach is commonly used in CAS to determine emergent properties, diffusion modelling has traditionally taken an aggregate-level approach, and as such may not have been as well-suited for handling emergent diffusion situations. As computational power has increased in recent decades, more bottom-up forecasting approaches have begun to emerge in adoption studies, focusing on increased use of behavioural and socio-economic models to capture real-world complexities and more individualistic behavioural traits. However, the calibration of these more complex forecasting techniques can often prove to be a challenge, meaning careful consideration is required of the datasets used to train any numerical or analytical methods used. If incorrectly calibrated, forecasts (of any kind) can produce results that appear statistically significant, but do not actually produce logical arguments [Government Digital Service, 2013b, Swan, 2008, Office of Technology Assessment and Congressional Budget Office, 1984]. A good forecast is dependent on having accurate and complete data, so it is advised that as much effort is spent on ensuring that data meets the modelling requirements as making the model itself [Swan, 2008, LeBoff, 2001]. The use of both top-down and bottom-up forecasting methods can help here through triangulation to verify overall forecasting trends, by confirming whether all projections are aligned.

The classic technology adoption model that segments populations into innovators, early adopters, early majority, late majority, and laggards was created by Rogers in 1957 [Rogers, 2010]. This is illustrated in Fig. 2.33. The gradual proliferation and saturation of a new technology within a market (shown by the cumulative number of adopters curve in Fig. 2.33) corresponds to the second of the two S-curves described in section 2.1 (see Fig. 2.3 and Fig. 2.4). The close relationship between technology development and diffusion models of consumer adoption is typically characterised by the overlaps shown in Fig. 2.4 and Fig. 2.34. The model shown in Fig. 2.34 provides a slightly more detailed view of the cross-over between these domains, and shows that once a technology reaches a certain critical maturity (when it is deemed ‘good enough’), market forces and user experience take over any further technological development.

In Rogers model, diffusion occurs explicitly through communication channels, with regions of overlapping heterogeneous networks being the most prolifically active. In these regions, diversity across interlinked structures of social relations, values, and behavioural motivations provide multiple stimuli that shape adoption trends [Dattée and Weil, 2007, Rogers et al., 2005]. This has since been empirically validated by policy innovation diffusion studies in the USA, where states with the most diverse populations show the highest probability of implementing policy innovations. The model implies that nonhuman intervention devices, such as mass media, need to be incorporated into diffusion models to represent communication channels [Rogers et al., 2005]. Additionally, the degree of cultural similarity or difference between connected entities (homophily or heterophily respectively) can have a large impact on the ease of diffusion. A greater degree of homophily allows for rapid diffusion [Dattée and Weil, 2007, Rogers et al., 2005, Deffuant et al., 2000], although a degree of heterophily is required for reactivity in adoption. Accordingly, the influence individuals may have on the adoption tendencies of others around them has been represented as proportional to the difference in opinions by some studies (such as Deffuant [Deffuant et al., 2000]) when the difference is below a certain threshold.

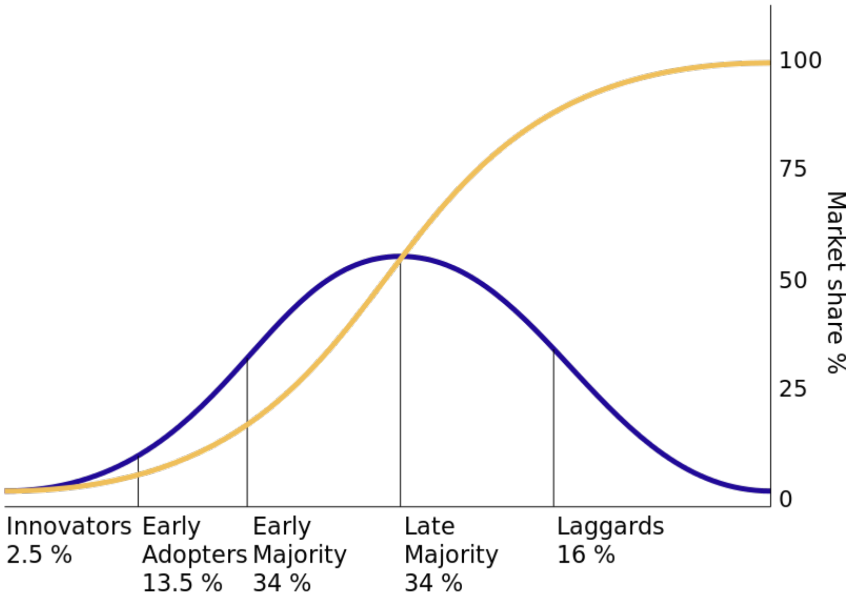


Figure 2.33: The diffusion of innovations according to Rogers [Rogers, 2010]

However, assuming absolute proportionality would suggest that extreme values of heterophily can make diffusion almost impossible [Rogers et al., 2005], which may not take into account the impact polar opposite opinions can have on each other's behaviour (such as between opponents in political debates). More generally, the study by Rogers identified that adoption of innovations occurs more rapidly if the innovation is perceived as:

1. relatively advantageous over ideas that preceded it;
2. compatible with existing values, beliefs, and experiences;
3. relatively easy to comprehend and adapt (although this requires resources to do so);
4. observable or tangible (see Constant's arguments regarding quantifiable evidence in section 2.2);
5. divisible (i.e. separable) for trial.

Building on the work of Rogers, one of the most commonly employed predictive models of technology adoption was generated by Frank Bass in 1969 [Bass, 1969]. Forecasting techniques such as the Bass diffusion model [Bass, 1969, 2004] are often applied (amongst numerous other techniques; Peres et al. [2010], Xie and Levinson [2007]) to gauge the impact of new products and technologies within markets, or estimate substitution patterns observed as successive generations of technology replace existing dominant designs (see Fig. 2.1) [Foster and Rosenzweig, 2010]. The original Bass model states that the probability that an individual will adopt the innovation, given that the individual has not yet adopted it, is linear with respect to the number of previous adopters, and is given as:

$$\frac{dF}{dT}(t) = (p + qF(t))(1 - F(t)) \tag{2.1}$$

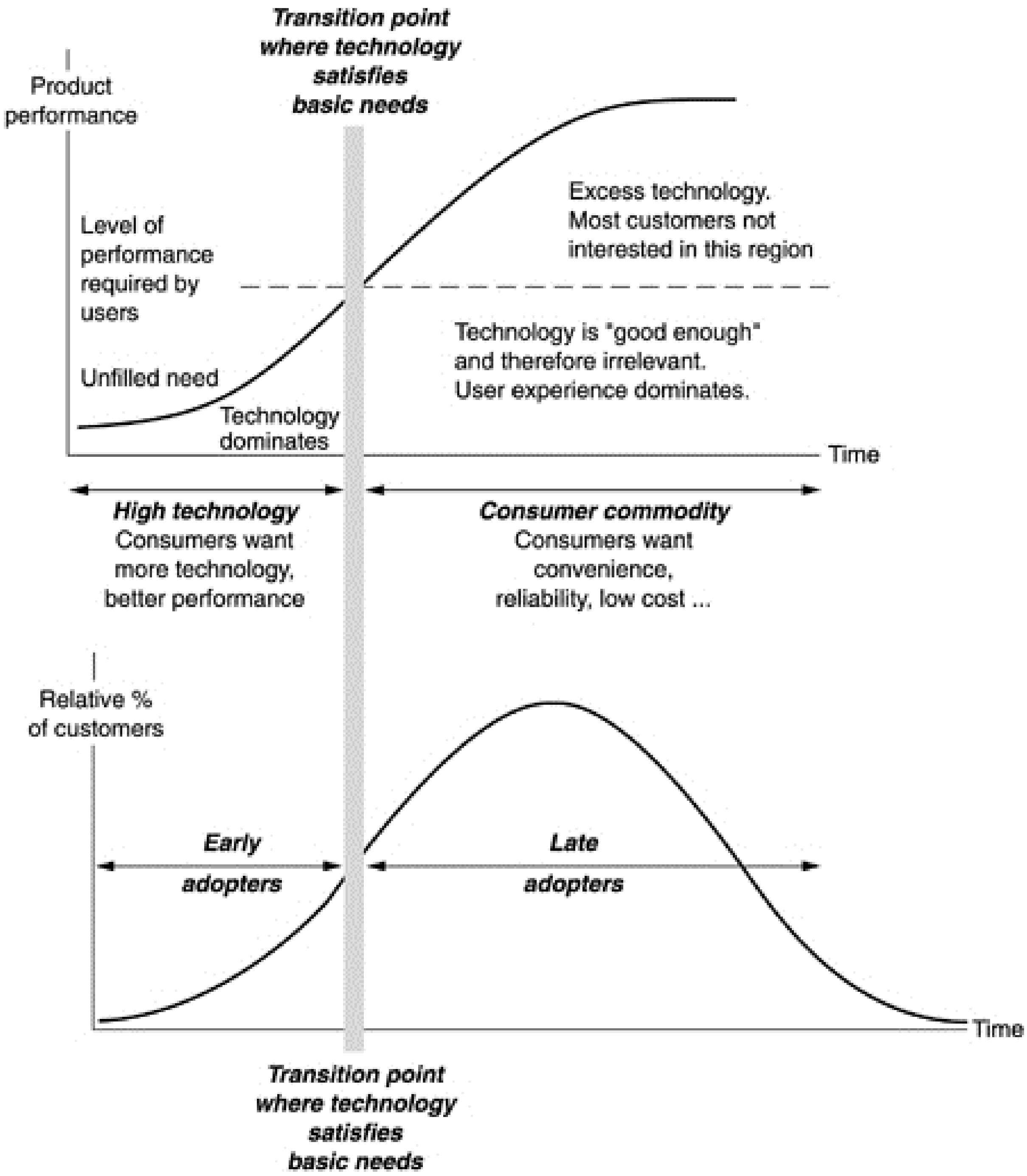


Figure 2.34: The transition from technology-driven to customer-driven products [Norman, 1998]

where $F(t)$ is the installed base fraction, p is the *coefficient of innovation* (representing the individuals' external influences: advertising, mass media, etc.), and q is the *coefficient of imitation* (representing the individuals' internal influences, i.e. from social interactions among adopters and potential adopters in the system). The precise values used for these coefficients are usually generated from "guessing by analogy", meaning that accuracy of the model is often limited by the amount of data available for analogy when the forecast is made. This model treats external influences similar to a force acting on adopters, with the pressure to adopt increasing with the number of previous adopters [Bass, 2004]. A closed-form solution of the Bass model is given by:

$$F(t;p;q) = \frac{1 - e^{-p(p+q)t}}{(\frac{q}{p})e^{-(p+q)t+1}} \tag{2.2}$$

with the final population of adopting entities often referred to as m. This basic Bass model originated from mathematical models of contagions, however this and other aggregate-level models do not consider the determinants that influence individual adoption decisions. As such, aggregate-level models are not an exact representation of the actual targeting of marketing activities which are normally focused at the individual level [Chatterjee and Eliashberg, 1990, Peres et al., 2010]. Consequently, these models are typically well-suited to modelling large populations. Nevertheless, since manufacturing organisations may be comprised of large numbers of people (who may on an individual basis support or oppose a new technology) it is still possible to represent a small numbers of organisations using these models.

The initial Bass model has now been extended to handle diffusion of successive technology generations, and to include tailored decision variables such as price and advertising whilst maintaining the basic diffusion curve [Bass, 2004]. The illustration shown in Fig. 2.1 demonstrates one such application of the extended Bass diffusion model, in this case comparing simulated and observed sales for the introduction of successive generations of DRAM computer chips between 1974 and 2000. Many other studies have since developed the concepts proposed by Rogers and Bass, such as the extension from a deterministic to a stochastic representation in the work of Niu [Niu, 2002]. This states that anomalies previously considered as independent random errors (when considering aggregate models versus actual empirical data), may result from stochastic variation inherent in the process of adoption.

As the classic Bass diffusion model uses a simple aggregate level formulation, this assumes that all entities in a network are homogeneous (i.e. the probability of any agent adopting from one time period to the next remains unchanged) and fully connected. This assumption has been contended by more recent models such as Chatterjee, Dattée, and Goldenberg, who study diffusion through heterogeneous populations and through socially disjointed networks, including heterogeneous initial conditions [Dattée and Weil, 2007, Chatterjee and Eliashberg, 1990, Goldenberg et al., 2001], as well as through empirical studies such as Rogers [Rogers et al., 2005]. In the Agent Based Modelling (ABM) work of Chatterjee, a utility theory accounts for individual adopter preference under uncertain performance in a monopolistic setting (rather than under competing candidate technologies), along with Bayesian modelling of perceptions of performance and price (where price and functionality are assumed to be known at model outset, although this would be unlikely in reality) [Chatterjee and Eliashberg, 1990]. Once an agent adopts the technology, it is removed from the subpopulation of potential adopters, and individual adoption times are aggregated for the total simulation to generate an overall technology penetration curve [Chatterjee and Eliashberg, 1990]. In this model, agent risk aversion to performance is modelled as a utility function as:

$$u_x(\tilde{x}_i) = 1 - e^{-c\tilde{x}_i} \tag{2.3}$$

where $\tilde{x}_i$ is the potential adopter's uncertain perception of performance after receiving i "units" of information (assumed to be normally distributed), and c (> 0) is the coefficient of risk aversion. The utility function is scaled so that $u_x(0) = 0$, and results in increased utility of the technology as uncertainty reduces [Dattée and Weil, 2007, Rogers et al., 2005, Chatterjee and Eliashberg, 1990], with several models showing uncertainty itself reduces as a result of increased visibility [Dattée and Weil, 2007, Rogers et al., 2005]. Using a fixed price, $\bar{p}$, of the innovation, Chatterjee calculates the potential adopter's utility for the innovation using a widely accepted additive utility function:

$$U(\tilde{x}_i, \bar{p}) = k_x u_x(\tilde{x}_i) + k_{\bar{p}} u_{\bar{p}}(\bar{p}) \tag{2.4}$$

where k_x and $k_{\bar{p}}$ are scaling constants (or importance weightings) associated with uniattribute utility functions for performance and price respectively. From this, Chatterjee deduces a condition which results in consumers adopting the innovation as soon as individuals' expectation of performance exceeds the sum of the foreseen risk and price hurdles [Chatterjee and Eliashberg, 1990]. Chatterjee also identifies conditions under which the micro-modelling approach reproduces diffusion patterns generated by aggregate-level models. These conditions are shown in Table 2.4 [Chatterjee and Eliashberg, 1990].

Empirical validation of Chatterjee's micro-level approach showed a forecasting accuracy improvement in comparison to aggregate models, and a predisposition of early adopters to rely on external sources of information for their decisions more than later adopters (consistent with literature on innovation [Rogers, 2010, Dattée and Weil, 2007, Chatterjee and Eliashberg, 1990, National Academy of Engineering, 2013]). Chatterjee suggests however that traditional Bayesian learning models may not completely fit observed empirical evidence, as they do not take into account the credibility of information received. Consequently, Chatterjee accounts for this by including variance on the effectiveness of 'information' generating processes, determining a critical information threshold for each agent's adoption. The distance from this threshold shows how far an agent is from adoption [Chatterjee and Eliashberg, 1990]. This model does not, however, account for benefits perceived by new or alternative functionalities.

The systems dynamics model produced by Dattée studied the dynamics of substitution (rather than diffusion, which assumes no generational influences) in a heterogeneous, partially connected social structure, where substitution specifically includes dynamics relating to obsolescence, vested interests, and underlying struggles. By directly modelling a time lag in innovation performance versus the expectations of potential adopters of the system, Dattée suggests that it is possible to predict non-trivial substitution patterns (beyond the scope of the original Bass model) as well as a wide variety of commonly observed human behaviours such as surprise, disappointment, enthusiasm, hype, and overshooting (see Fig. 2.2 and Fig. 2.4) [Dattée and Weil, 2007, Linden and Fenn, 2003, Amara and Lipinski, 1983]. This model assumes consumers will make a decision whether to adopt based on the top four or five attributes that individuals most highly rank, based on their own personal preferences and experience, and then apply either a conjunctive or disjunctive decision rule for reaching an

Table 2.4: Conditions under which micro-modelling approach reproduces aggregate diffusion models [Chatterjee and Eliashberg, 1990]

		Our Model: $A(t) = \psi_I + \psi_{II} F\gamma(i(t))$; $i(t) = nt$	
Differential Equation for Penetration Rate	Cumulative Penetration	Distribution (c.d.f.) of γ across Segment II ($0 \leq \gamma < \infty$)	Segment Sizes and Relationships among Parameters
	Model: Bass (1969)		
$dA/dt = (p + qA)(1 - A)$ $A(0) = 0$	$A(t \mid p, q) = \dfrac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}$	Logistic: $F_\gamma(\gamma \mid a, b) = \dfrac{1 - e^{-a\gamma}}{1 + be^{-a\gamma}}$	$\psi_I = 0, \psi_{II} = 1$ $p = an/(1 + b)$ $q = abn/(1 + b)$
	Model: Fourt and Woodlock (1960)		
$dA/dt = p(1 - A)$ $A(0) = 0$	$A(t \mid p) = 1 - e^{-pt}$	Exponential: $F_\gamma(\gamma \mid a) = 1 - e^{-a\gamma}$	$\psi_I = 0, \psi_{II} = 1$ $p = an$
	Model: Mansfield (1961)		
$dA/dt = qA(1 - A)$ $A(0) = A_0, 0 < A_0 < 1$	$A(t \mid q, A_0) = \dfrac{1}{1 + \left(\dfrac{1 - A_0}{A_0}\right)e^{-qt}}$	Logistic: $F_\gamma(\gamma \mid a, b) = \dfrac{1 - e^{-a\gamma}}{1 + be^{-a\gamma}}$	$\psi_I = 1/(1 + b), \psi_{II} = b/(1$ $q = an$ $A_0 = 1/(1 + b)$
	Model: Gompertz (Martino 1975)		
$dA/dt = qA \ln(1/A)$ $A(0) = A_0, 0 < A_0 < 1$	$A(t \mid q, A_0) = (1/A_0)^{-e^{-qt}}$	Truncated extreme value: $F_\gamma(\gamma \mid a, b)$ $= \left[\dfrac{1}{1 - F_0}\right][e^{-e^{-(\gamma - a)/b}} - F_0]$ where $F_0 = e^{-e^{a/b}}$	$\psi_I = F_0, \psi_{II} = 1 - F_0$ $q = n/b$ $A_0 = F_0$

outcome[1]. Other more recent models by Goldenberg have employed cellular automata to simulate individual-level diffusion processes (in a similar manner to Chatterjee), since numerical solutions are generally more powerful and accurate than traditional equation solving. This also provides a visual way to present dynamically changing complex systems. In Goldenberg's 2001 study, social systems of over 1,000 potential adopters were considered and analysed in nearly 5,000 different diffusion processes. Sensitivity analysis of even larger simulations suggested that a social system of 1,000 agents was sufficient to generate the complex dynamics required from the model. Goldenberg's initial simulation used the relationship below to calculate the probability of adoption, $PA(t)$:

$$PA(t) = [1 - (1 - p)(1 - q)^{k(t)}] \tag{2.5}$$

where p and q are adapted from the original Bass diffusion model to represent the probability that in a certain time period an individual will be influenced by external mechanisms to adopt the innovation,

[1] Conjunctive rule requires that an innovation scores highly on each attribute the individual considers, whilst disjunctive rule means that only one attribute has to pass a critical threshold for adoption.

and the probability that they will be influenced by an interaction with another individual. Here $k(t)$ is the number of previous adopters at time t. Goldenberg's results indicated that the cellular automata model can replicate the Bass model well (in agreement with Chatterjee's ABM approach [Chatterjee and Eliashberg, 1990]), along with defined boundaries and expected variance for the equation determinants. The exception to this occurs when q values drop below a critical threshold, leading to a collapse of diffusion processes due to very low social interactions. In addition, this study showed a need for advertising beyond the take-off point in diffusion (in contrast to previous suggestions from Rogers [Rogers, 2010]).

An extensive review of recent literature on diffusion studies by Peres and Mahajan further challenged some of the original assumptions of the Bass diffusion model. This proposed that diffusion theory should be revised from its traditional perception of being a theory of interpersonal communication (such as "word of mouth" interactions), to include any form of social interdependence (including other *social signals* and *network externalities*) [Peres et al., 2010, Goldenberg et al., 2001] (see Fig. 2.35).

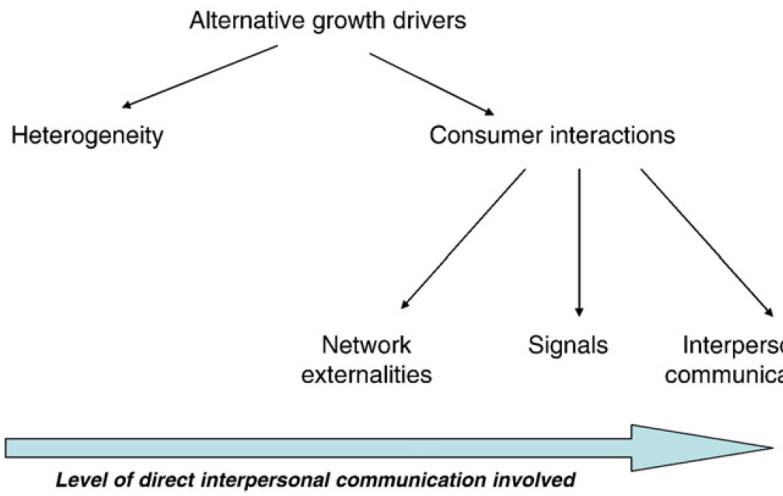


Figure 2.35: Market factors behind innovation diffusions [Peres et al., 2010]

Network externalities here refers to the increase in utility of a given product as adoption increases. This happens directly in most forms of telecommunication technology, or indirectly if the increase in the number of adoptions of a technology improves the chances of adoption of a complimentary product (i.e. DVD sales supporting the value of DVD players). *Social signals* describe information that can be inferred from an individual adopting an innovation by demonstrating association with a particular brand or product family (such as Apple iPhone users, etc.). Table 2.5 provides a summary of additional findings from this review on the latest directions and proposed extensions in diffusion theory research [Peres et al., 2010].

Equally, products themselves convey information to new users. The diffusion of information as a result of a new technology can sometimes have a negative effect on adoption, as users suffer from data overload and loose productivity screening additional information. This effect can be amplified by the integration required between humans and technology, with more involved processes requiring increased time for productive use [Andolfatto and Smith, 2001, David, 1991]. This raises the question of the

Table 2.5: Diffusion research focus and future research directions [Peres et al., 2010]

	Subject	Research focus	Directions for further research
Diffusion within markets and technologies	Diffusion in social networks	The roles of central individuals such as influentials and experts Individual-level modeling using agent-based models and social network concepts	Incorporating findings on individual decision-making from behavioral studies and choice experiments into diffusion modeling The influence of social network characteristics (e.g., clustering) on diffusion patterns Measuring the effects of word-of-mouth campaigns Explicit representations of word of mouth and signals Use of data and tools from social network researchers
	Diffusion and network externalities	Types of externalities (direct vs. indirect, local vs. global) Incorporating externalities into the diffusion model The impeding and enhancing effects of externalities on the speed of diffusion	Network externalities in partially connected social networks Understanding the network externalities that bring about a tipping point
	Takeoffs and saddles	Defining takeoffs and saddles Determinants and international comparisons of takeoffs Measurements of the size and frequency of saddles Incorporating saddles into the diffusion framework	Combining pre- and post-takeoff growth in the diffusion framework Understanding the roles of heterogeneity and internal influences in takeoff and saddle formation
	Technology generations	Acceleration of diffusion parameters across generations Multi-generational diffusion models	Combining behavioral and modeling research to understand technological substitution Optimal timing for the release of a new generation Advanced methods to improve forecasting accuracy
Diffusion across markets and brands	Cross-country influences	Multi-national diffusion models Estimation of the magnitude of cross-country influences Optimal global entry strategies	Diffusion of innovations in the developing world
	Growth differences across countries	Differences in diffusion parameters across countries and their cultural and economic sources	Differences between western and emerging economies Effects of demographic changes (e.g., immigration waves) on diffusion
	Competition and growth	Models of competitive diffusion including category and brand level influences The effects of disadoption and churn	The interaction between individual brand choice processes and diffusion (1-step vs. 2-step process) Influence of competition on the distribution chain and the effect on diffusion

learning requirements associated with a given technology for potential adopters. The more recent work of Mäkinen supports Rogers' perception-based enablers [Mäkinen et al., 2013] in this regard. In Mäkinen's study, an aggregate-level systems dynamic model of company level innovation adoption is created, including resource allocation that follows dynamic changes based on the Bass model of diffusion [Bass, 2004]. In Mäkinen's model, adoption of innovations is considered as technological learning at multiple levels: learning by doing, learning by studying and developing, and learning by imitation (the latter often empirically observed in commercial groups). Using this model to analyse the diffusion of new computer processing chip requirements across game developers, Mäkinen showed that companies tend to imitate the behaviour of other organisations in adopting technology early, rather than innovating themselves and learning by using. Mäkinen concludes that this signifies innovation and learning by using are not the main drivers of accelerating adoption, but this result may be more of an industry-specific outcome since processor chip development has not yet reached a crisis (at which point more radical approaches may be considered that encourage widespread innovation, or learning by using).

Considering more general applications of diffusion studies to LTS, the "productivity paradox" is identified in the work of David and Ruttan. This refers to conditions where the growth anticipated for a new GPT is not observed, or in some cases not measurable, until some years after initial release, as revised metrics are not available and previous metrics do not emphasis new benefits. This is thought to result from the extended diffusion and distribution of technologies to a critical number of *heavy users* first [Ruttan et al., 2008, David, 1991], consistent with historical observations of a number of revolutionary technologies [Ruttan et al., 2008, David, 1991]. For example, this was observed with computers in 1989 when only 2% of global business information was digitised, yet computers were assumed to be prevalent in most industrialised nations [David, 1991]. In many historical cases, anticipated productivity boosts were not observed until a dominant model of a GPT emerged (with sufficient variations catering for the majority of the population), and technology diffusion had passed a critical 50% threshold [David, 1991]. In this manner, societies' expectations of a new technology often increase faster than natural rates of technology diffusion (also confirmed by Dattée [Dattée and Weil, 2007]), meaning this perceived lag can also limit the number of technology applications [David, 1991]. Other societal variations in LTS include aspects such as imbalanced regional adoption behaviours, where emerging economies may not adopt technological systems following the same historical growth patterns witnessed previously in mature markets [Oum et al., 2013]. This has consequently been identified as an area for increased focus in more recent diffusion studies (see Table 2.5).

Information credibility also plays an important role in adoption in LTS due to different motivations of new technology advocates (where heavy users may not be considered trustworthy by all), and the technological paradigms they promote [Yu and Singh, 2002]. Therefore, models of reputation and trust are also viable components to consider, based on their influence on adoption trends. In one example, Yu incorporates elements of fraud and deception in an agent-based model of cooperation behaviours in an LTS (useful for competitive markets), where agents begin as equals and form credibility ratings of other agents based on referrals from third parties. This employs a Bayesian framework with Dempster-Shafer calculus. Agents use collected referrals to decide whether to cooperate with another agent [Dattée and Weil, 2007, Rogers et al., 2005, Yu and Singh, 2002], and, if aware of their own reputation growth, agents can start to abuse their influence in a technological system. Consequently, the reputation of the agent (which was previously high) begins to decrease, until it is possibly isolated. The model also indicates that the reputation of agents behaving well or badly in a smaller community will change faster than those of similar agents in a larger community (where 'bad' agents' reputational damage is more rapidly forgotten), and that communities will collapse if the ratio of non-cooperative agents to cooperative agents becomes too high [Yu and Singh, 2002]. Therefore, credibility and trust in social networks can be gained through favourable social behaviour, conforming to existing norms [Rogers et al., 2005], consistently demonstrating increased performance, or reinforcing messages sent by other independent agents. Similar to the work of Chatterjee, Constant, and Kuhn, this supports the need for some form of credibility metric when considering adoption influences [Chatterjee and Eliashberg, 1990, Constant, 1973, Kuhn, 1996].

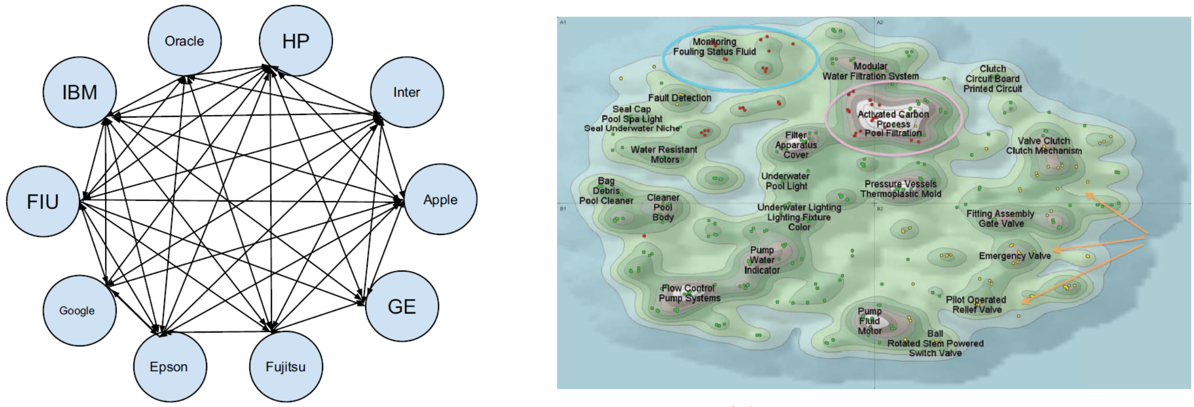
2.8 Patent analytics and patent-based technology forecasting

Prior analysis of historical technological developments has suggested that patent data can be observed to account for 90 to 95% of all of the world's inventions [Liu and Shyu, 1997, Chen and Chen, 2007]. However, the length and complexity of many patents means that a considerable amount of time is often required, even for domain experts, to read and analyse a single patent document [Zhang et al., 2015]. Whilst the structure of a patent document is typically well-defined, analysis is complicated by the prevalence of domain-specific technical and legal terminologies in the description of the invention [Zhang et al., 2015]. The patent content is also conveyed in large amounts of unstructured text or snippets that are often fragmented, obscure, or ambiguous [Zhang et al., 2015]. Human errors, such as spelling mistakes, add to this complexity, and influence the precision and recall of patent searches

[Stein et al., 2012]. These issues make it challenging therefore to quickly ascertain the core idea of a patent. As a result, considerable research has focused on techniques to reduce both the structural and lexical complexity of patents using information retrieval, data mining, and natural language processing techniques, amongst others [Zhang et al., 2015]. The work of Shinmori et al. provides one such example of how structural complexity may be reduced through the use of natural language processing [Shinmori et al., 2003]. In this study, six contextual relationships (relating to *procedure*, *component*, *elaboration*, *feature*, *precondition*, and *composition*) are used to capture and structure information in Japanese patent claims. Combining this with cue-phrase-based approaches, a structure tree is generated to represent the first independent claim, with experimental results indicating improved accuracy over previous approaches for the same dataset [Shinmori et al., 2003]. Sheremetyeva extends this tree-based approach to capture both the structure and lexical content of U.S. patents by decomposing long claim sentences into short segments, prior to analysing the dependency between segments. In this way, a tree-based representation is created that reproduces the content and structure of the claim in a more readable format [Sheremetyeva, 2003]. Techniques such as these can therefore enable improved comprehension of individual patent claims, but for a more global view of technology domains it is necessary to examine the relationships between patents. The relationships between patent documents can be established in many different ways, depending on the types of information considered. Information stored in patent documents can often be grouped into two primary categories (in a similar manner to many other data sources): structured and unstructured items.

Structured items in patents adopt a uniform format as well as standardised semantics [Zhang et al., 2015]. Typically these include fields such as the patent number, details of inventors and assignees, and the filing and issue dates [Zhang et al., 2015]. Domain-specific trends can subsequently be built from these fields using existing data mining techniques. Equally, citation graphs generated from this data enable the discovery of interesting patterns linked to specific patent documents, making this a frequently adopted tool for visualising patent dependencies (a typical example of a patent assignee citation graph is shown in Fig. 2.36). Citation analysis has also been shown to provide the clearest indicator of the value, potential, and impact of a given patent through examinations of bibliographic coupling (where two patents are found to share one or more citation), and co-citation analysis (where two patent documents have been cited by one or more patents) [Albert et al., 1991, Huang et al., 2003]. These techniques for establishing patent value from structured citation data can be further enhanced through the use of ranking-based approaches, such as Fujii's use of the PageRank algorithm to calculate citation-based scores for patent documents [Brin and Page, 1998, Fujii, 2007].

Unstructured fields, on the other hand, contain text of varying lengths, as may be found in fields relating to the claims, abstracts, and description of the invention [Zhang et al., 2015]. This data does not lend itself to the extraction of trends in the same way as structured fields, but is more often coupled with text mining techniques to generate patent maps and landscapes. This data provides a valuable compliment to document correlations established from structured data analysis, since it provides rich information on the core ideas contained in patents [Zhang et al., 2015]. Consequently, unstructured data forms the basis of content analysis. Content-based patent maps have some notable advantages over citation analysis when it comes to the extraction of latent information in patents and visualising global



(a) Patent Assignee Citation Graph (Source:NodeXL)

(b) Water Patent Landscape Map (Source:CleanTech)

Figure 2.36: Representative examples of patent visualisation [Zhang et al., 2015]

technology domains, whilst at the same time reducing the dependency on domain knowledge expertise [Zhang et al., 2015]. Typical forms of patent maps generated from unstructured text include technology vacuum maps, claim point maps, and technology portfolio maps [Yoon et al., 2002], such as the patent landscape map shown in Fig. 2.36. The sophistication of these landscapes have increased in recent decades, with the use of concept-based maps. The work of Atsushi et al. illustrates this concept-based approach, where word-concept matrices are derived from the decomposition of word co-occurrence matrices, before being transformed into a landscape map through the hierarchical clustering of document concepts [Atsushi and Yukawa, 2004]. Technology vacuum maps provide an alternative perspective on patent landscapes, highlighting gaps in current developments through the observation of large blank, and sparsely populated, zones in domain maps. One such example is provided by Lee et al., where principal components analysis has been used to reduce the keyword feature space into a suitable format for a two-dimensional map [Lee et al., 2009]. In addition to patent landscape reviews, content analysis of unstructured data also extends to automatic search query generation and the evaluation of the technical strength and novelty of inventions. For example, experimentation has shown that using terms from different sections of a patent document, and weightings based on term frequency, can produce higher-quality search queries that achieve superior retrieval performance [Mahdabi et al., 2011, Xue and Croft, 2009b, Konishi, 2005]. Meanwhile, Hasan et al. used content analysis based on natural language processing to extract key phrases from the claims section of patent documents in order to subsequently calculate originality scores for each document [Hasan et al., 2009]. This approach has since been adopted by IBM, and expanded to assess the concept behind a patent rather than specific words or phrases, to prevent deterioration in the rationality of scoring arising from possible term ambiguity [Hu et al., 2012].

By coupling analysis of both structured and unstructured patent data it is therefore possible to describe the general picture of the targeted technology domain alongside the evolutionary progress of the technologies included within that domain. Such a procedure has been demonstrated in the work of Kim et al. [Kim et al., 2008]. This begins by translating keywords from patents in a given technology domain into representative keyword-based vectors for the documents considered. Clustering is then performed on these documents, to construct a semantic network of keywords, which is subsequently transformed into a patent map by rearranging each keyword node according to its earliest filing date and frequency within the considered patent documents [Kim et al., 2008]. Natural language processing provides one potential means of patent map generation based on this coupled approach by allowing bibliographic information, such as assignee details and filing date, to be integrated with the analysis of other unstructured content [Yoon et al., 2013]. This is in contrast to traditional technology vacuum maps, which are purely based on unstructured patent content [Zhang et al., 2015]. As such, coupled approaches enable greater understanding of technological competition trends when formulating R&D strategies [Zhang et al., 2015].

Beyond improving techniques for exploring complex patent claims and mapping the dependencies between documents, the automatic classification of patents also represents a significant area of research. Whilst the sophisticated hierarchical structures, verbose content, rhetorical descriptions, and wide variety of topics considered by patents pose major challenges for automatic classifiers, the huge volumes of documents available provides ample material for both supervised and unsupervised learning approaches. As such, classification has become a key area of application for machine learning within patent analytics. This has commonly involved the training of classifiers based on the bag-of-words (BOW) model, where the frequency of each word in unstructured text defines profile features for matching between documents. Starting from this premise, a study by Larkey proposed a classification scheme that combined the BOW model with KNN (K-Nearest Neighbours) and naive Bayes classifiers, establishing the KNN-based classifier as the best performer [Larkey, 1998]. The performance of alternative classification algorithms for categorising patent documents was subsequently compared in the work of Fall et al. This included evaluation of naive Bayes, Support Vector Machine (SVM), KNN, and Winnow algorithms, concluding that the best performance for class-level patent categorisation was obtained using SVM based on the first 300 words of the description [Fall et al., 2003, 2004]. Later studies have also observed significant improvements in classification through the use of more advanced machine learning classifiers. For example, a KNN-based model that calculates patent similarity based on both term frequency and semantic tags was shown to achieve a 74% improvement over prior approaches in Japanese patent classification [Kim and Choi, 2007].

However, machine learning applications extend beyond initial patent classification in filing offices. Other applications include learning models used to automatically generate search queries, such as in the "learning-to-rank" model based on patent structure and retrieval-score features proposed by Xue and Croft to improve information retrieval [Xue and Croft, 2009a]. Similarly, clustering and regression-based approaches have been used to determine the relevance of retrieved documents as in the works of Bashir and Rauber, and Mahdabi et al. respectively [Bashir and Rauber, 2009, Mahdabi and Crestani, 2012]. Learning models have also been proposed for assessing the patentability of new patent applications, to determine the likelihood of acceptance or rejection, as in the feature-based binary classification scheme developed by Hido et al. based on historical Japanese patent examination data [Hido et al., 2012]. This again demonstrated improved performance in predicting examination decisions compared to prior methods. Other studies, such as those of Jin et al. and Liu et al. use court judgements alongside feature recognition and learning algorithms to assess the quality of patents and consequently predict the likely value and outcome of maintenance decisions related to each patent [Jin et al., 2011, Liu et al., 2011b].

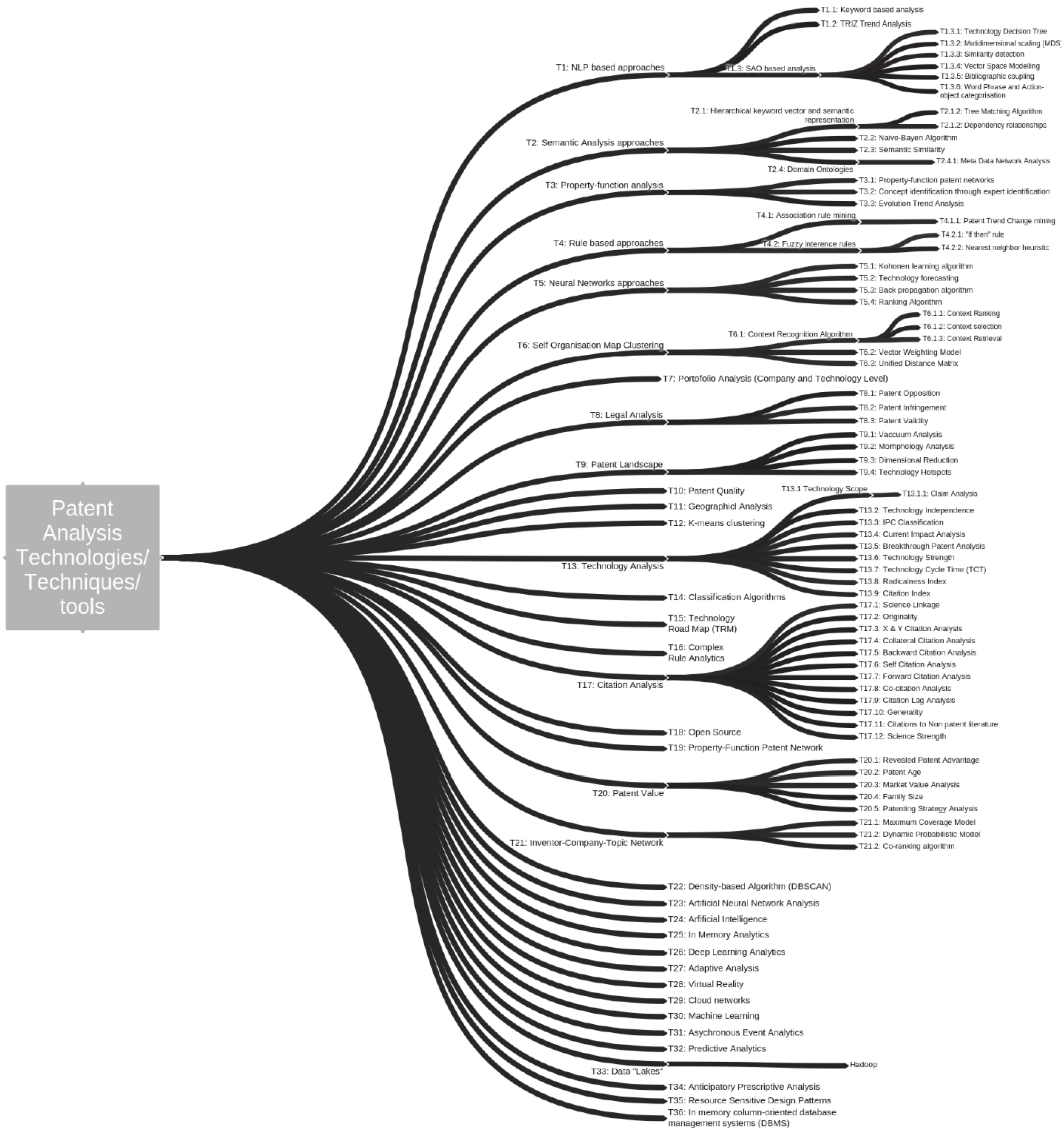


Figure 2.37: Patent analytics technologies, techniques, and tools [Aristodemou et al., 2017]

The versatility of these learning approaches with respect to patent analytics can be seen more globally through the technology impact assessment produced recently by the University of Cambridge's Centre for Technology Management (see Figs. 2.37 and 2.38). Here, different analytic techniques have been assessed relative to their ability to tackle five key domain problems in patent analytics. These domain problems relate to:

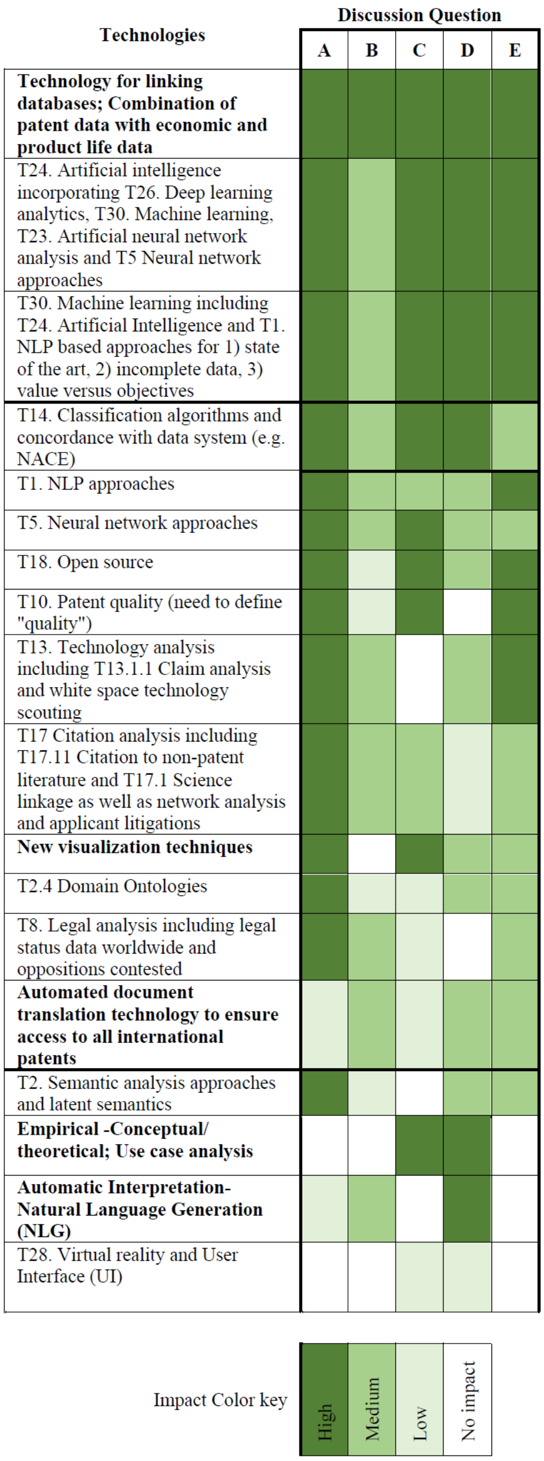
a) Patent data pre-processing
b) Ensuring interconnectedness and compatibility between patent databases

c) Enabling effective data analysis
d) Effective visualisation of patent information
e) Determining patent quality and identifying invalid patents

From this it can be seen that existing machine learning and artificial intelligence methods are expected to play a core role in future developments of patent analytics. Equally, this assessment highlights the contribution emerging techniques such as deep learning are expected to make in this field in the future [Aristodemou et al., 2017].

The use of patents for forecasting technology development trends, and the close links to economic activity, has evolved considerably since the earliest literature was published on measuring innovation from patent statistics by the likes of Schmookler and Scherer in the 1960s [Schmookler, 1966, Scherer, 1965]. More recent publications have expanded these early concepts and demonstrated on numerous occasions how patterns in historic patent data can be used to build predictions of future development trends, including using partially complete or mined datasets when historical data is not yet available. Many of these studies attempt to assess the development maturity of a given technology (not to be confused with measures of commercial market adoption [Adner and Kapoor, 2015, Edgerton, 2011]) against commonly recognised milestones and features in observed technology evolution patterns. Chief amongst these is comparison to Arthur Little's *Technology Life Cycle* (TLC) [Little, 1981]. Comprising four stages (*emergence*, *growth*, *maturity*, and *saturation*), Little's framework describes a means of measuring technological development efforts relative to a technology's competitive impact and progress in transitioning from product to process-based innovation.

Classically, TLC studies have relied on simple counts of patent records to determine the maturity of technologies on this scale. However, contesting the accuracy and reliability of matching a single patent indicator against pre-determined growth curves, Watts, Porter, and Haupt advocated the use of multiple patent metrics in their technology evaluations [Watts and Porter, 1997, Haupt et al., 2007]. Building on this, Gao demonstrated the use of a trained nearest neighbour classifier, based on 13 extracted patent data dimensions, to assess a technology's life cycle progress [Gao et al., 2013]. This was followed more recently by Lee's proposal for the use of a stochastic method based on multiple patent indicators and a hidden Markov model (i.e. an unsupervised machine learning technique) to estimate the probability of a technology being at a certain stage of its life cycle [Lee et al., 2016]. In parallel to these extensions to sets of indicators and pattern recognition techniques, the use of text-mining approaches to improve speed, relevance, and accuracy of patent analysis methods has been demonstrated by Ranaei's automatic retrieval of patent records for forecasting the development of electric and hydrogen vehicles [Ranaei et al., 2016]. Similarly, patent content clustering techniques for technology forecasting purposes have been explored by the works of Trappey and Daim [Trappey et al., 2011, Daim et al., 2006]. Daim's analysis illustrated how technology forecasting results for emerging technologies can be improved by combining patent-based statistics with bibliometric clustering and citation analysis techniques for the purpose of data acquisition (as a proxy indicator for technology diffusion when historical data is unavailable). However, being able to determine the technical readiness of a new technology is only part of the forecasting problem. The other critical aspect that must be



Notes: Dark color indicates high impact, whereas blank indicates no impact. Technologies in bold are new technologies identified, whereas all the others are priority technologies. Technology numbers (T1 etc.) refer to the technology numbering shown in Figure 2.37

Figure 2.38: Relevance of new technologies to known patent analytics challenges [Aristodemou et al., 2017]

considered is the market adoption of the technology once it has been commercialised [Adner and Kapoor, 2015, Edgerton, 2011]. Here, Daim's work subsequently coupled the patent-based and academic literature data-mining techniques employed with the use of system dynamics modelling, to explore causal relationships and non-linear behaviours in technology diffusion.

2.9 Conclusions from literature review

To explore and clearly define the research domain to be considered in this study prior to formulating the research problem and research strategy, this chapter has considered numerous different facets of technology substitution. The first of these relates to the characteristics and theoretical background behind technology substitutions. Here it was noted that the introduction of new technologies is conventionally represented using S-curve growth models (inspired by biological systems), along the lines of the Fisher-Pry model. A founding assumption of many of these growth models is that technologies ultimately arrive at a limiting condition based on physical constraints. However, in reality, technology development often stalls for a range of different economic, social, and technical reasons, making it difficult to ascertain if a physical limit has actually been reached or if this is merely a temporary blip. This makes it important to understand the nature of the 'failure' that may lead to a substitution.

In this regard, three existing definitions of technological failure were considered relating to social marginalisation from a range of cultural and societal influences, humanity's ever-increasing performance expectations, and the divergence of opinions that means a technology may be a failure in some people's eyes but not others. These definitions of failure emphasise the need to consider both social and technical issues faced by a stagnating technology, to determine if its full potential has really been achieved, and equally the need to understand what is meant by 'success' for a given technology. A definition of technological failure for this study is subsequently provided that focuses on periods of either temporary or more sustained stagnation which permits a new technology to emerge. Temporary periods of stagnation may correspond to unfruitful development efforts at the time or lack of market interest, which in turn could create a false impression elsewhere of having reached the technology's ultimate physical limit. In many situations, this will subsequently have been proved to be untrue. However, the flip-side of these perceived technological failures arises when presumptive leaps lead to substitutions occurring before, or just as, an incumbent technology has reached such a performance plateau. In these conditions, Edward Constant prescribes the appearance of presumptive anomalies based on scientific insight that anticipates the eventual failure of the existing technology before any functional-failure has taken place. Such anomalies, which on their own might only be dismissed as a limiting condition to the normal technology, can lead to technological crises when a quantifiable alternative technological system also exists, exposing the relative failing of the existing technology. This review concludes that to identify cases of technological substitution arising from presumptive anomaly, a modelling framework would need to identify if a functional failure already exists, and if new scientific discoveries have preceded such a failure. In this sense, presumption is assumed to relate to conditions where a functional-failure does not already exist prior to the transition, whilst reactive substitutions are in response to an already observed failure. Consequently, a technology substitution modelling framework needs to consider a population's awareness of the:

a) current rate of scientific development associated with new technologies [Constant, 1973];
b) current rate of technological development associated with new technologies [Constant, 1973];
c) potential extension opportunities of both new and existing technologies (e.g. credible alternatives are believed to exist) [Constant, 1973, Adner and Kapoor, 2015].

These findings also give rise to certain validation criteria that a technology substitution model needs to fulfil:

1. Recognition of a current or future market for a replacement technology can arise from either a) or b) even if no functional-failure has yet occurred (e.g. recognition of either a possible future limiting condition for the existing technology or spontaneous emergence of an alternative technology).
2. Adoption can only be predicted as a result of presumption if a), b), and c) are all considered [Constant, 1973, Adner and Kapoor, 2015].
3. Adoption can still occur if there is no presumption, but this happens as a result of the accumulation of issues, challenges, or obstacles associated with technological anomalies [Constant, 1973].
4. Presumptive effects can be quantified by contrasting adoption curves for technologies believed to have transitioned from one technology to another as a result of gradual technological failure with those believed to be examples of a presumptive shift.

The third point above signifies that if issues linked to technological anomalies are resolved at a fast rate or accumulate slowly, adoption remains at a low level, with some adoption still occurring as a result of perceived technological failure (in line with the third of Gooday's failure definitions). Conversely, if these challenges are resolved at a slow rate (i.e. anomaly-related events accumulate), adoption increases as a result of more wide-spread perceptions of technological failure.

Considering the dynamics of the substitutions themselves, a common feature noted in many ideas of technological substitution and revolution is critical mass, emphasising the non-linear nature of adoption processes once market characteristics prove favourable. A small number of successful backers can make the critical difference at this stage, providing they have sufficient influence and power over other segments of the market (which is often the case in Large Technological Systems which are hierarchically structured and nested). As more revolutionary substitutions take place, the transition from *normal science* and *normal technology* to more radical approaches is accompanied by a shift in behavioural traits in scientific and technological communities, who move from a *puzzle solving* to a *puzzle definition* mode of operation. In this sense, substitutions may represent a period of greater exploration. Some substitutions have led to the creation of new general purpose technologies (such as the internet as a means of information transfer), which spawn new industries and complementary technologies. This adds to the complexity of the dynamics expected, with reverse salients appearing in areas where performance gaps are holding back progression of the new technology. When known solutions fail to resolve these lagging elements of a technological system, functional-failure becomes recognisable. Additionally, the frameworks needed to support these general purpose technologies help to explain skills and resource dependencies apparent for substitutions in LTS, which need to be considered when determining the take-off point in adoption for many of the technologies in this study. Equally, the goals and diversity of domain experience of the creative group behind the innovation can play important roles in shaping how technology performance develops over time, and therefore the dynamics of the substitution as it moves between the seven stages of evolution outlined by Hughes.

A conceptual framework for classifying substitutions that considers both the *emergence challenges* facing new technologies and *extension opportunities* still available to existing technologies, proposed by Adner, provides a basis for separating technologies into more reactive or presumptive modes of substitution. This framework could equally be used for distinguishing sub-modes of *creative destruction*, *robust coexistence*, *resilience illusion*, and *robust resilience*, but this would require additional evidence for corroborating assigned labels that would not necessarily be available. Consequently, this is not proposed here, but left for future extension. Applying Adner's framework accordingly, along with the concepts of technological failure, anomalies, and crisis defined in sections 2.1 and 2.2, literature evidence has subsequently enabled classification of the technologies considered in this study as a basis for subsequent pattern recognition analysis.

Next, the bibliometric indicators of scientific and technological development were considered. Measures of scientific production such as publication counts were identified as being more suitable on this occasion than purer measures of scientific progress (such as citation analysis) when investigating perceptions of progress. This is because models of technology substitution require an understanding of motivations and behaviours behind adopter decisions, meaning that any model constructed needs to combine measures of knowledge contribution with the socio-technical influences typically observed in the adoption and diffusion processes. This includes general awareness of the advances made, and the influence of population size and *word-of-mouth* effects. In this manner, scientific and technological progress do not necessarily equate to the tendency to adopt.

Models of technology adoption, such as the classic Bass diffusion model (and extensions) were then reviewed. Building on the work of Rogers and Bass, subsequent developments have demonstrated strong links between performance, credibility, availability of skills and resources, the effectiveness of communications, hierarchical social structures, and economic success when new technologies are considered for adoption. Equally, more recent studies have incorporated network externalities to show how the value of a technology may increase as more adopters share the same platform.

Lastly, existing patent analytics and patent-based forecasting techniques were considered alongside their connection to measures of technological maturity (such as the Technology Life Cycle defined by Little). More recent approaches have introduced content analysis, machine learning, and pattern recognition techniques, whilst coupling bibliometric analysis with the use of approaches such as system dynamics to explore the causal relationships behind technology adoption and diffusion. In a similar vein, based on Constant's hypothesis regarding scientific and technological anomalies and their influence on the mode of technological substitution, and a simplified version of Adner's technology substitution framework, this study looks to test whether bibliometric measures of scientific and technological development can provide an indication of the likely mode of adoption. The framing of this research problem is discussed in more detail in the next chapter.

Chapter 3

Formulating the research problem and research strategy

By considering research in fields relating to technology diffusion, substitutions, and the use of scientific and technological measures in a forecasting context, the research problem and strategy for the current study are now formulated. This chapter outlines the methodological influences and assumptions that have structured the work that follows. Philosophical and methodological issues are considered first, followed by the main research hypothesis, research questions, and problem structuring methods. From this, the data acquisition and modelling strategy is defined, alongside the principal literature, topics, and expected capabilities that shape the overall project.

3.1 Philosophical and methodological issues

As a large aircraft manufacturer in the global ATS, Airbus provides a significant number of the commercial jet aircraft in service around the world, and plays an important role in shaping future forms of air travel and the aviation industry. The increasingly complex nature of the ATS means that sophisticated models are required to understand the impact technology will have on this LTS [Hughes et al., 1987], particularly in the case of technological substitutions. This research project is intended to explore the causes of technology substitutions, their observed dynamics, and develop the capabilities for modelling these events whilst taking into account broader socio-technical influences. The Problem Structuring Methods (PSMs) discussed here are intended to define the main challenges for the study to address, with the goal of developing a suitable modelling framework for aiding the strategic evaluation of future technological innovations.

Recent studies have increasingly attempted to fuse both qualitative and quantitative approaches together, to target research efforts more effectively within problem spaces considered (often referred to as methodological pluralism). A clear explanation of methodology is therefore required, to describe the logic behind choosing either a qualitative or quantitative approach, to readers from both *hard* and *soft* technical backgrounds (often associated with either classical or social science disciplines respectively). This also explains the route from desired research values and purpose, to problem definition and the final communication of results with the intended recipients of the research. This is particularly relevant when considering hard engineering disciplines, as long-established methodologies can often be assumed by default, without necessarily questioning the broader consequences of methodological choices, or the possible soft system implications. In this context, emphasis is not often placed on the preceding methodological rigour.

To begin, it is important to acknowledge the author's own subjectivity, as this affects the final conclusions presented (either positively or negatively). This is unavoidable, as it is impossible to remove the scientist from the research. Equally, it is important to consider the philosophical beliefs of other authors when reviewing their work. For example, conflicts of interest exist between different schools of thought which may be shaped by authors' motivations or targeting of specific audiences. Moreover, the understanding shared by existing publications varies based on the philosophical predisposition of the reader. The researcher's subjectivity places biases on any conclusions drawn, as the information summarised is based on each person's interpretation of what the critical points are that should be communicated. For instance, the findings in chapter 2 arise from the author's view of relevant literature, and are influenced by his subjective interpretation of the material.

Several spectrums are examined to describe philosophical outlooks. These include the conflicting extremes posed by objective and subjective stances, deductive and inductive reasoning, generalisable versus specifically tailored problem solutions, and formal versus informal recording styles. On these scales, the author believes that his philosophical outlook, shaped by educational background as well as personal and professional experiences, tends to follow a preference for an objective, inductive, generalisable, and informal approach. However, subjectivity has also been applied in the scoping of this research, based on existing familiarity with more quantitative approaches. Equally, the philosophical stance outlined above is not applicable to all aspects of this work, but represents the author's preferred tendency. This equates more to a phenomenological approach to research, as the author is generally inclined to explore areas not previously covered in depth by other studies or industries, and is cautious of trying to refute existing theories (as in more positivistic approaches) when little is often known with absolute certainty. Consequently, the author prefers to focus on the exploration or development of new fields to generate further understanding and theories. This is perhaps in contrast to the harder systems background conventionally presented, and often unstated, in aeronautical engineering (the author's original discipline), which tends to be much more ontologically focused than epistemological (i.e. *"these things are known"* versus *"this is how we know them"*).

In reality, the author's current systems-thinking perspective is likely located between positivistic and phenomenological philosophies, due to previous work on operational research, and global beliefs in ecological and sustainable causes. It is important to consider these two scientific paradigms, as the adopted philosophy determines the compatibility of different research strategies. For example, the phenomenological mindset often encountered in operational research encourages strategies based more on grounded theory [Glaser et al., 1968, Corbin and Strauss, 1990, Partington, 2000] and modelling approaches to be used. These techniques place greater emphasis on searching for patterns emerging out of datasets, rather than overlaying an expected pattern and trying to find a match. The difficulty with these approaches is in ensuring that findings can be shown to be reliable and generalisable, which may require repeating simulations numerous times to identify patterns at higher levels of abstraction. Conversely, a researcher following a purely positivistic or reductionist approach may not see the value of unintended outcomes. As such, they may not try to build these into their initial model assumptions, expectations, or final conclusions to the same extent, instead focusing on refuting what is already known. This is the difference between assuming that *'the purpose of the system is what it is intended to do'* rather than *'the purpose of the system is what it does'* (POSIWID). Ultimately these research paradigms can be mixed based on the particular research question of interest.

In the context of the current research topic, technological substitutions are dependent on a range of adopters' perceptions and actions. To capture the diversity of perceptions and socio-technical influences within a population, ontological statements of *'what the world is'* should ideally be avoided. Consequently, purely positivistic theories are likely to be difficult to resolve in this instance. As adoption trends are driven by behavioural traits displayed by individuals and communities, an inductive approach typical of *'big data analytics'* is thought more practical here for capturing and reproducing observed behavioural characteristics. This is also more likely to support the discovery of new behaviours and causal influences, rather than disprove existing behavioural models, in line with previously stated phenomenological assumptions. Consequently, the preference here is to apply an objective interpretation of inductive methods (in this case, data mining approaches), with some limited hypotheses of expected behaviours.

3.2 Study hypothesis

Considering the motivation for this study (outlined in chapter 1), conclusions from literature evidence (outlined in chapter 2), and the philosophical background discussed above, the principal study hypothesis is now formulated. This speculates that technology substitutions may follow one of two principal substitution modes, driven either by performance expectations or relative scientific and technological development efforts, and that it is possible to recognise these modes through the emergence of patterns in available technology datasets. In doing so, a company such as Airbus would obtain a more robust and resilient strategic outlook for the short, medium, and long-term future, enabling the company to innovate strategically and confidently. This study is consequently hoped to be an innovation enabler and decision-making aid. The null hypothesis of this would be that no clear distinction exists between substitutions based on performance expectations and relative scientific and technological development efforts, meaning that it is not possible to detect any clear modes of substitution through the available data. In this condition the research would have no direct impact on long-term robustness for the company's product and service portfolio, but could still provide an indirect benefit to decision-making through eliminating one source of uncertainty associated with measures of technological development. In either case, a measure of success for this study is that the results provide guidance to decision-makers, which in turn enhances their effectiveness.

3.3 Overview of Problem Structuring Methods applied to the research project

An initial summary of the problem structuring elements and research path used throughout the project is illustrated in Fig. 3.1. This illustrates how both soft and hard systems perspectives are applied to explore the research project, to ensure that subsequent interventions are properly focused, based on clearly defined research objectives.

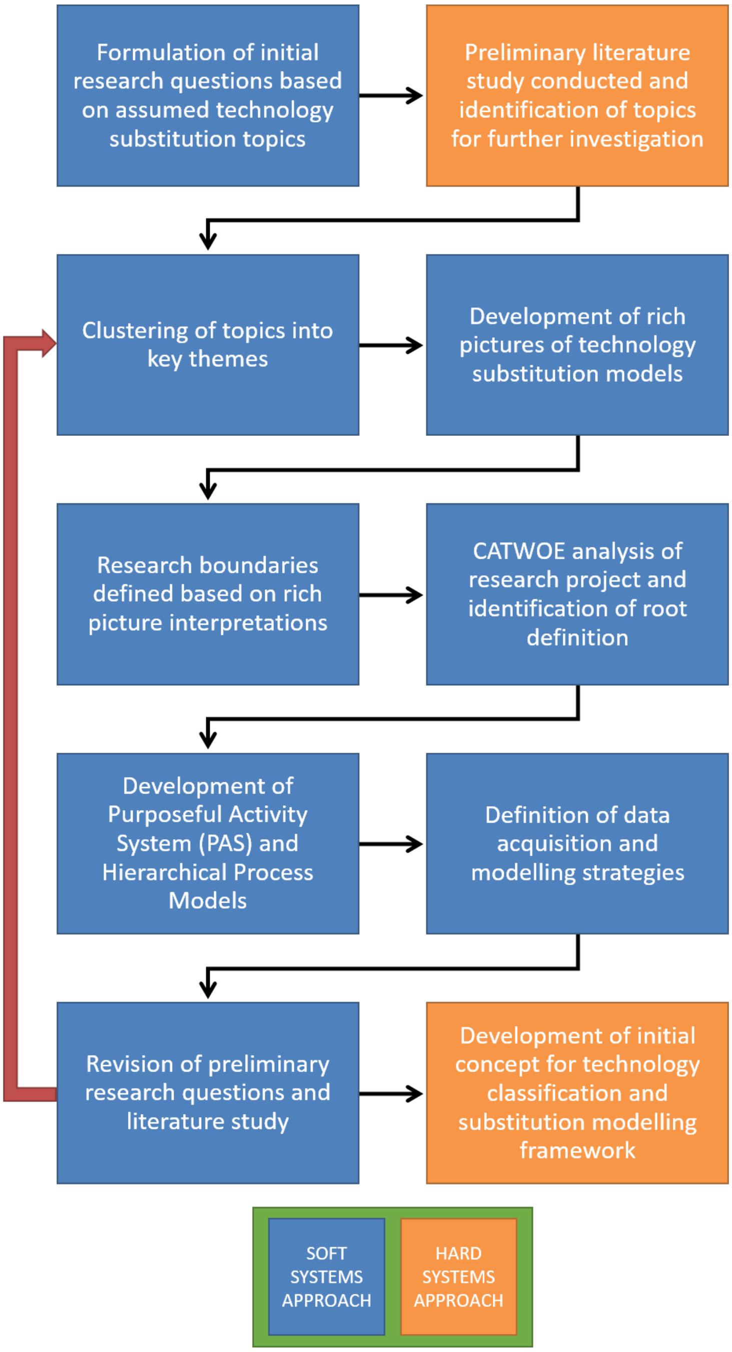


Figure 3.1: Application of problem structuring methods to research project

The socio-technical influences considered within technology diffusion means that both interpretivist and more traditional functionalist philosophies were applied when structuring the research strategies in this project. This was as a result of intangible and idiosyncratic features that make it difficult to generalise adoption behaviours with exact precision, as may be suggested by more conventional reductionist approaches. Equally, the major aim of this research is to gain an understanding of phenomenon occurring in technology substitutions as a decision-making aid, without providing an exact forecast (a considerably more complex task considering the number of autonomous entities involved). Diagnostic and exploratory approaches are equally beneficial here, alongside more functionalist optimisation techniques [Burrell and Morgan, 2017]. In terms of practical application, this means that the research approach (outlined in Fig. 3.1) and data acquisition and modelling strategy (discussed in section 3.6) mix both interpretivist soft systems methodologies (such as the generation of *rich pictures*, *CATWOE* analysis, *purposeful activity systems*, and *hierarchical process modelling*) with more functionalist methods (such as *systems dynamics*) for detailed modelling of technological substitutions. The following sections discuss the main activities represented in Fig. 3.1 in more detail.

3.4 Application of Soft Systems Methodology to the research project

To define the boundaries of the study, Soft Systems Methodologies (SSMs) based on those outlined by Checkland [Checkland, 2000] were applied, to explore the socio-technical influences that need to be considered in technology substitution.

3.4.1 Research questions

There is a need for using structured research questions in academic studies to give focus to complex topics that could otherwise expand to encompass an incomprehensible range of disciplines. Consequently, research questions should be structured such that answering them adds to knowledge directly, whilst being open enough that they can be answered in many different formats. This provides an interesting contrast between academic and industrial requirements, where an enterprise-based approach prefers to see very specific questions being addressed. The questions outlined in Table 3.1 show the eventual research focus converged on through an iterative development process shared with the research objectives outlined in chapter 1, literature review in chapter 2, and problem structuring methods considered in this chapter. Preliminary research questions, based on topics originally envisaged as central to the overall research direction, provided the starting point for structuring the earliest literature searches, before subsequent refinements generated the questions presented in Table 3.1.

3.4.2 Application of Situation Mapping

Methodological rigour requires a structured mapping between problem field definition, research paradigms, and research questions. Using the preliminary research questions to identify disciplines related to performance expectations or relative scientific and technological development efforts on the

Table 3.1: Main research questions (left) and supporting questions (right)

1) What does a technological substitution look like?	A) How do technological innovations diffuse across large technological systems?
	B) What are the characteristics of technological substitutions?
	C) What impact do different types of technological substitutions have on adoption dynamics?
2) To what extent are technological substitution dynamics dependent on scientific foresight?	A) How are scientific and technological progress measured?
	B) What are the characteristics of technological anomalies?
	C) How are technological anomalies and performance stagnation related to technological substitutions?
	D) How viable are technology substitution models based on data-driven substitution classifications?

mode of technological substitutions highlighted the works of Kuhn and Constant on the nature of technological revolutions [Kuhn, 1996, Constant, 1973]. From these sources, a first attempt at depicting the relationship between technological failures and technology substitutions was generated, visualising in the form of a network the stages leading from pre-paradigm, to normal, and potentially revolutionary science phases. This is shown in Fig. 3.2.

Based on graph representations introduced by network sciences, the conceptual model shown in Fig. 3.2 translates the different stages of scientific evolution into a map of network dependencies between *puzzles* and *theories*. In this representation, the shape of the node indicates whether the node is referring to a *scientific puzzle* or a *scientific theory*. *Puzzles* (shown here as blue diamonds) are initially detected in a given scientific field before either forming the basis for a new *theory* (shown here as circles), or remaining as an unresolved anomaly (shown here as red diamonds). The size of each theory node is then scaled based on the degree of connectivity to other theories, whilst a colour spectrum is used to indicate the current credibility of any given theory. The snapshots in time shown in states 1 to 6 then illustrate how the scientific domain evolves over time through the linking and reinforcing of puzzles and theories, and how this pattern of evolution shifts as confidence in central tenets changes.

To begin with, in the *pre-paradigm phase* (state 1) there is no particular consensus on a central theory that links different theories and puzzles together. Instead, multiple incomplete and incompatible theories coexist at this point. If a conceptual framework emerges (state 2), a phase of *normal science* begins with the scientific network expanding as theories are steadily linked either directly or indirectly to the central paradigm. Anomalies occur during this time, but are generally resolved (state 3). In the event that a significant number of puzzles remain as unresolved anomalies, bolder scientists may begin to re-examine underlying assumptions (entering into a *revolutionary science* phase), leading to the

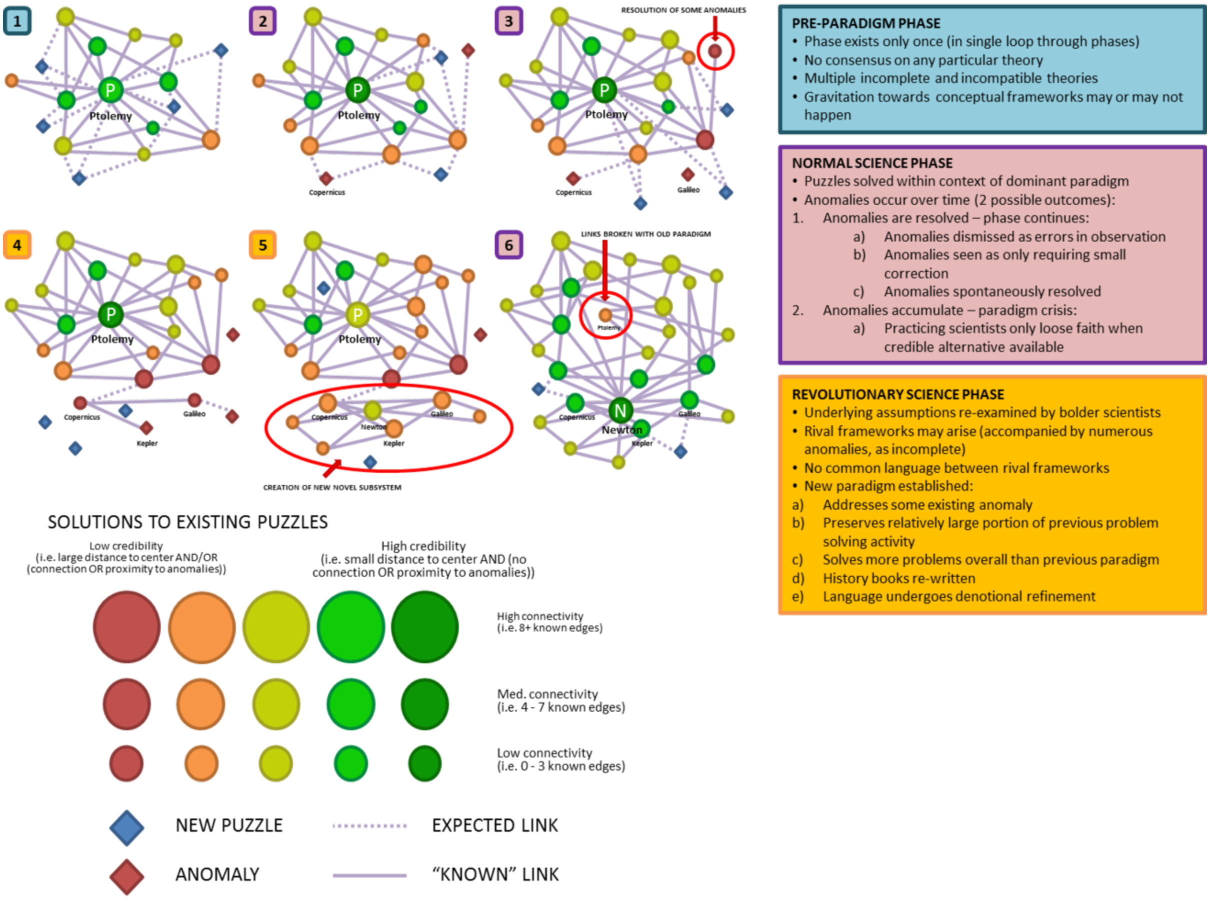


Figure 3.2: A network illustration of technological revolution as a result of technological failure (based on the work of Kuhn [Kuhn, 1996])

detection of further anomalies and puzzles (state 4). This can lead the broader scientific community to question the credibility of the current dominant theory, potentially increasing the credibility of novel subsystems proposed to address known anomalies (state 5). If a relatively large portion of previous problem solving activity can be accounted for by a novel subsystem that addresses a particular anomaly, and more problems can be solved overall, this theory then becomes the new dominant paradigm and *normal science* resumes (state 6). Fig. 3.2 therefore provided a means of relating preliminary research questions to notions of *puzzle solving*, *puzzle definition*, *technological anomalies*, and *technological revolutions* highlighted in the works of Kuhn, Constant, and Hughes [Kuhn, 1996, Constant, 1973, Hughes et al., 1987]. At the same time, this provided a more intuitive representation of the characteristic evolutionary states of scientific domains.

As the research questions and literature review were progressively refined, a clearer image of the research domain began to take shape. In this regard, Fig. 3.3 visualises a more comprehensive view of the problem space associated with technology substitution modelling in a rich picture format, and how principal concepts fit into this interpretive picture.

This illustration presents the author's view of the topics associated with technological substitutions, and the dependencies to consider for each topic. In this diagram the coloured clusters of topics broadly relate

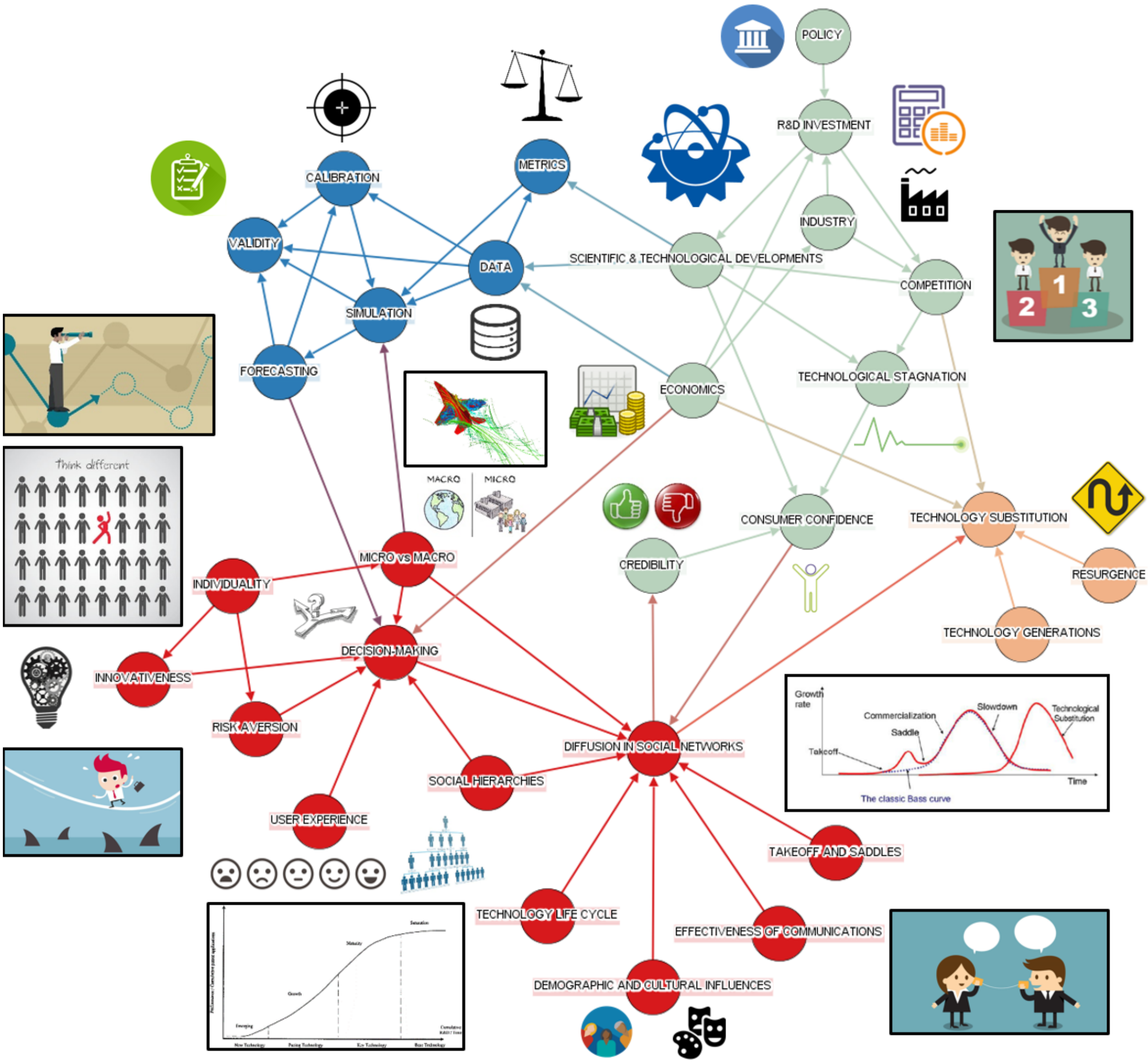


Figure 3.3: Technology substitution modelling context

to key themes of *modelling and simulation* (blue), *technological development* (green), *time dynamics* (orange), and *social and organisational influences* (red). Fig. 3.3 was subsequently used as a means to explore potential features to include when structuring research efforts, and areas where control or influence could be applied. The process of creating the rich picture aided in narrowing the scope of the original problem to the more specific research boundaries outlined in Table 3.1 and Table 3.2.

Although this simple representation is illustrative of factors associated with technological substitution, it is certainly not exhaustive. This is because it does not portray all actors, elements, relationships, or perspectives of technology substitution that are observed in the real-world. Equally, the current study is focused on those elements most relevant to large technological systems, and consequently adopts a predominantly vendor-based perspective. Consumer needs, demand, and technology acceptance considerations such as those that may be found in the relevant literature for consumer electronics products do not therefore apply here. However, as a visual framing and communication device for

Table 3.2: Definition of research boundaries

Endogenous	Exogenous	Excluded
• Calibration • Consumer confidence • Credibility • Decision-making • Diffusion in social networks • Effectiveness of communications • Forecasting • Metrics • Scientific & Technological developments • Simulation • Take-off and saddles • Technological stagnation • Technology substitution • Validity	• Competition • Data • Economics • Industry • Risk aversion • Social hierarchies • Technology Life Cycle	• Demographic and cultural influences • Individuality • Innovativeness • Micro vs Macro • Policy • R&D investment • Resurgence • Technology generations • User experience

exploring the fundamental problem domain, this situation mapping process proved to be a valuable aid. Much of this value came from providing a means of communicating boundary assumptions to research project stakeholders and peers (with diverse interpretations of the project), and capturing additional perspectives not previously anticipated. Incorporating the plurality of views in this manner [Jackson, 2003] helped to limit the scope of the problem to common areas of interest.

3.4.3 Application of Soft Systems Modelling

To define an appropriate research strategy for understanding the modes associated with technology substitutions, a *CATWOE* and root definition structuring exercise was completed based on the desired transformation process (shown in Fig. 3.4), the rich picture formulated for technology substitution modelling (shown in Fig. 3.3), and the guiding principles outlined and discussed in [Checkland, 2000]. The results of these processes are shown in Table 3.3 with the research project mission statement below.

Figure 3.4: Research project transformation process

Table 3.3: CATWOE analysis used to structure the root definition and overall research project [Checkland, 2000]

CUSTOMERS	1. Airbus strategic decision-makers *(Airbus product policy team, Airbus R&T organisation, Airbus corporate level policy-makers)* 2. Agile Wing Integration consortium 3. Future Projects Office (FPO) teams: • Cost Analysis Engineers • Manufacturing Engineers • Overall Aircraft Design teams *(Design + Performance roles)* • System Engineers
ACTORS	1. Research engineer 2. Academic and industrial supervisors
TRANSFORMATION PROCESS	Developing the capability to identify and test the sensitivity of the mode of substitution for emerging technologies in the Air Transportation System (ATS)
WORLDVIEW	Decreasing returns on investment for incremental aviation product/service development means new concepts of operation and technologies will have to be implemented to enable future growth. Large uncertainty exists around the opportunities presented by new technologies and the robustness of existing technologies, making decision-making complex, slow, and expensive. Having capabilities for identifying likely modes of substitution and market impacts will reduce uncertainty in decision-making processes, reduce time-to-market, and allow robust product/service strategies (i.e. roadmaps) to be developed
OWNERS	1. Future Projects Office project managers 2. Airbus R&T organisation
ENVIRONMENTAL CONSTRAINTS	1. Availability of technology datasets 2. Availability of market data 3. Market size and demographic trends 4. Global economic conditions 5. Modelling the laws of physics *(i.e. specific representations of technology functionality)* 6. Project budget and schedules

RESEARCH PROJECT ROOT DEFINITION

A process for the research engineer (A), sponsored by the Airbus Research and Technology organisation and Future Projects management team (O), to provide the capability to identify and test the sensitivity of the mode of substitution for emerging technologies in the Air Transportation System (T) to Airbus strategic decision-makers (C), by using data-driven models to reproduce observed adoption behaviours for categorised examples, in order to reduce uncertainty in decision-making processes, reduce time-to-market, and allow robust product/service strategies to be developed (W) in response to continually changing global demographic, economic, and physical conditions (E)

Having generated the research project root definition, the mission statement was consequently used as a basis for structuring the Purposeful Activity System (PAS) model in Fig. 3.5 and the Hierarchical Process Model (HPM) decomposition discussed in Section 3.5.

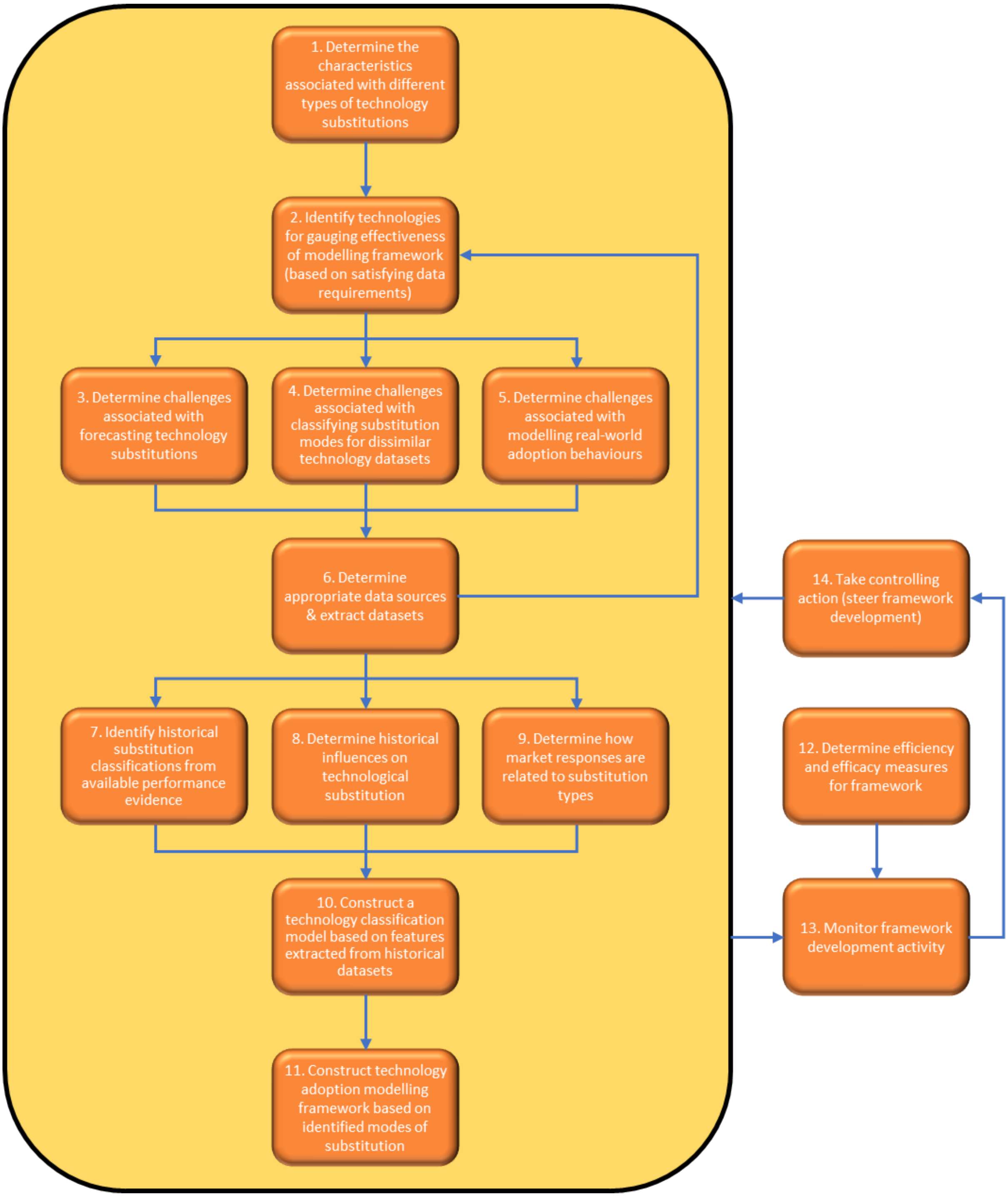


Figure 3.5: Purposeful Activity System (PAS) of the overall research project (based on concepts from [Checkland and Poulter, 2006])

Structuring the research project through these soft systems modelling techniques was a beneficial means of refining the example technologies considered and developing a sequential research agenda, by anchoring planned activities to a concise view of the project's overall aims. This made it significantly easier to ensure consistency between overlapping streams of research, and to bound each activity described within the PAS. However, there were challenges faced when developing these definitions, perhaps most notably in the case of settling on a final world-view within this systems modelling framework. This is potentially symptomatic of two of the commonly identified failings of the *CATWOE* process, which are the ambiguity of the terms used in the guiding principles [Checkland, 2000, Fairtlough, 1982, Basden, 2002], and the lack of theoretical underpinning behind the overall analysis [Mingers, 1992]. In this case, changing perspectives on both the overall aims of the project and proposed final outcomes from project owners made it difficult to identify a single world-view of what the final transformation process should achieve. As such, a considerable number of iterations were required, using the preliminary research questions as communication aids (holons), to converge on a feasible boundary definition for the project and outline the expected benefits of the research. In addition, even with supporting inputs from project owners and other consulted stakeholders, it is possible that important structural elements and activities will be missed in building the *CATWOE* and PAS pictures, or alternatively these may be limited to one overriding perspective when there is unequal distribution of power or attitudes [Jackson, 1991, Mingers, 1980]. As such, care has to be taken that the definitions generated are sufficiently rigid to allow subsequent project structuring to proceed meaningfully in the short-term whilst retaining flexibility to allow later revisions if required in the long-term.

3.5 Application of Hierarchical Process Modelling to the research project

Using the situation mapping, *CATWOE* analysis, and PAS presented in sections 3.4.2, 3.4.3, and Fig. 3.5 respectively, the HPM shown in Fig. 3.6 was generated based on [Davis et al., 2007, 2010].

This HPM was created by applying a systematic decomposition of the transformation process described in Fig. 3.4 and Table 3.3 into smaller constituent processes. Doing so provided a structured means, during research planning phases, of identifying the core research activities required. At the same time, this problem structuring technique also helped in determining the relative prioritisation of each process, and aided in capturing underlying modelling assumptions. This was based on an initial qualitative review of the literature evidence associated with different research topics, which provided an indication of how well a given process was currently understood. This assessment was captured by the colour-coded performance bar shown underneath each research activity in Fig. 3.6. If there appeared to be evidence showing that a process was already sufficiently well developed the performance bar underneath the activity would predominantly be green. By contrast, if the evidence seemed to indicate that an activity was poorly developed (i.e. not very robust or mature), this performance bar would be predominantly red. However, it is also necessary to capture the uncertainty associated with an activity that may not be reflected by the existing literature evidence. As such, perceived gaps in knowledge (where there seems to be little literature evidence to either support or deny that a process is well understood) are indicated via white spaces in these performance bars. Consequently, a performance bar which has some green and some red present, but is predominantly blank corresponds to an activity which has a lot of uncertainty associated with it. The qualitative assessments made at the bottom level of this structure were then cascaded back up to the middle and top level research activities to give an indication of relative task priorities.

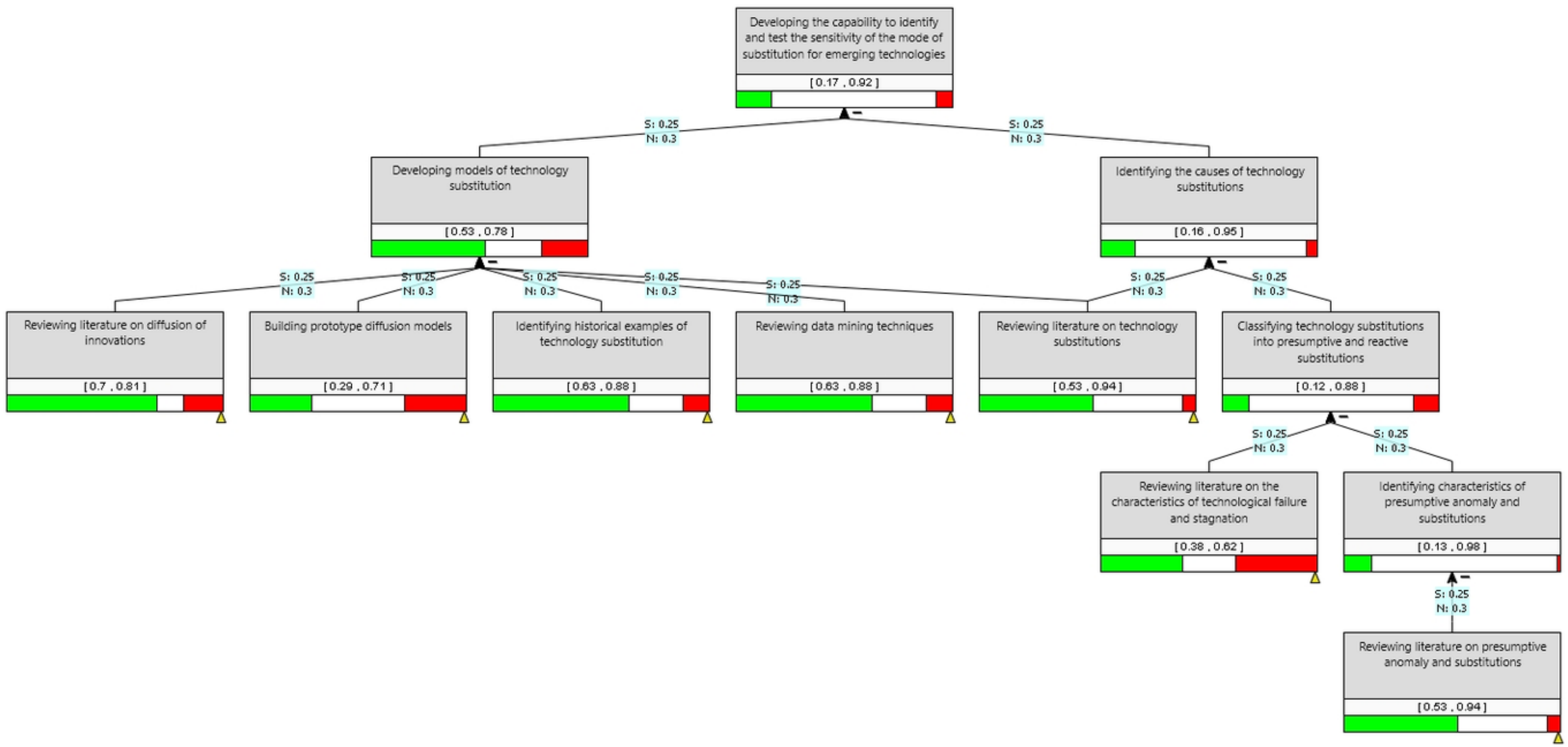


Figure 3.6: Hierarchical Process Model of the current research study (based on [Davis et al., 2007, 2010])

Table 3.4: Mapping of ideas and research topics to desired capabilities

CAPABILITY	Ability to locate and extract relevant historical technology datasets	Ability to compare dissimilar technology datasets	Ability to determine mode of substitution from available technology datasets	Ability to model reactive technological substitutions	Ability to model presumptive technology substitutions	Ability to test adoption sensitivity to mode of substitution
IDEAS	1.Data needs to be identified, extracted, and verified in a systematic manner 2.Bibliometric sources can be used to trace technology development 3.Patent databases often used as indicators of technological maturity	1.Pre-processing required to normalise datasets 2.Out-of-phase lifecycles mean feature alignment techniques required 3.Technology Life Cycle provides a means to identify common features	1.Data mining and pattern recognition techniques can be used for classification 2.Classification predictors need to be ranked in a systematic manner 3.Classification needs to be evaluated against technologies where historical evidence supports labelling	1.Adoption is based on perceptions of technological failure 2.Accumulation of technological anomaly-related events can indicate stagnation of the existing technology 3.Technological failure events can be represented using a Poisson distribution 4.Alternative technology has to be available for technological anomalies to become apparent	1.Adoption is based on scientific and technological developments 2.Presumption can arise from either scientific or technological developments 3.Presumption based on confidence levels associated with new and existing technologies	1.Automation makes modelling and simulation techniques less transparent than simpler methods 2.Modelling techniques need to be able to reproduce real-world behaviours 3.Modelling and simulation is sensitive to initial assumptions 4.Goodness-of-fit measures can provide basis for model calibration against historical adoption data
RESEARCH TOPICS	1.Technological paradigms 2.Bibliometrics 3.Measuring perceptions of science and technology 4.Patent-based technology forecasting	1.Large Technological Systems 2.Technology Life Cycle 3.Emergence 4.Statistical significance measures 5.Feature alignment	1.Substitution patterns 2.Technological anomalies 3.Pattern recognition 4.Time series classification 5.Cross-validation 6.Functional data analysis	1.Technology diffusion 2.Technological substitution 3.Technological failure	1.Technology diffusion 2.Technological substitution 3.Presumptive anomaly	1.Agent Based Modelling 2.System Dynamics 3.Verification and validation 4.Goodness-of-fit and summary statistics

For the current research project, the prioritisation showed that there was a high degree of uncertainty (and consequently risk) associated with tracing the causes of technological substitutions. Conversely, processes related to developing modelling frameworks appeared to be better understood, although not necessarily well implemented. Once generated the HPM highlighted the necessity and sufficiency of each constituent activity within the overall research strategy, based on the evidence available, enabling an evaluation of the most critical tasks to be completed [Hall et al., 1998]. Categorising the vulnerability of research activities in this manner ensures that sufficient effort is focused on exploring processes where there are indications of poor performance or large uncertainties (e.g. in this model, a need was identified to improve techniques for characterising technological stagnation). The decomposition method also helped to recognise other possible uses for the modelling framework besides the principal transformation process, such as providing a means to explore and test the causes of different substitution modes. However, as with the other SSMs applied, it is unlikely that this structure is exhaustive and that all perspectives and processes have been accounted for in the model, as only a small number of high level research activities are considered in Fig. 3.6. There are also questions relating to the validity of the linguistic evidence-based assessments made of each process, which are ultimately subjective and open to subsequent reinterpretation. Nevertheless, this technique provided a beneficial aid to the structuring of topics identified through group discussions, and determining options for resolving uncertainties (both aleatory and epistemic [Helton and Burmaster, 1996]) in higher level processes.

Using this HPM as a basis for targeting research activities guided the clustering of topics into more refined research streams. Consequently a summary of the research topics, ideas, and capabilities expected to satisfy prioritisations of research activities was generated, as shown in Table 3.4.

3.6 Data acquisition and modelling strategy

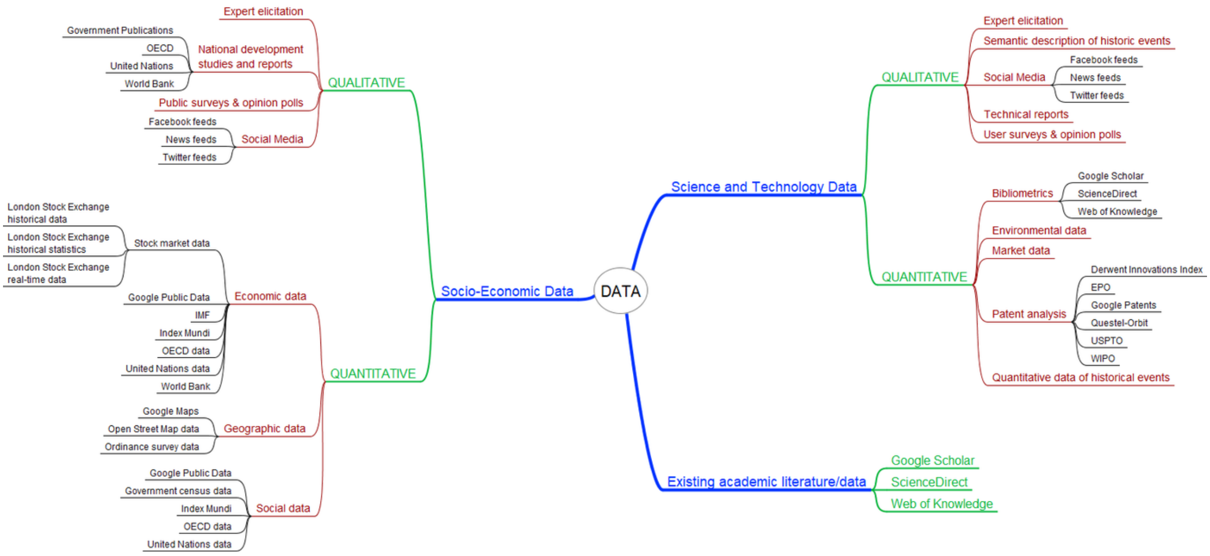


Figure 3.7: Data sources considered by research domain

To translate the research strategy outlined in Fig. 3.5 and Fig. 3.6 into a workable research method, it is necessary to consider the resources required to satisfy the transformation process described in Table 3.3. This relates principally to the types of data to be used, the means of acquisition, and the compatible model types that are available to subsequently structure and analyse the data (discussed in further detail in chapter 4). Depending on the type of data to be evaluated, a range of different techniques exist. Whereas quantitative data sources tend to be much more widely understood, with statistical and numerical procedures commonly relied upon, qualitative data sources have conventionally posed more of a challenge due to their more intangible nature. However, a variety of methods and tools have been developed to make sense of qualitative data sources, including structured and unstructured surveys, interviews, focus groups, narrative methods (i.e. storytelling), metaphors and artefacts, and ethnomethodology amongst others. In this regard, qualitative data sources often benefit from a phenomenological approach due to the subjectivity of these fields in contrast to purely quantifiable data sources. However, some parameters, such as the measure of a company's competitiveness, can be measured using both qualitative and quantitative data sources. For example, annual company financial reports can be evaluated in a positivistic sense through traditional cost-benefit approaches (amongst others), whilst competitiveness can be related to more intangible concepts such as brand loyalty, innovativeness, and the aggressiveness of the company. These softer dimensions may be better characterised through methods such as social media analysis (often supported by data visualisation techniques), or expert elicitation, etc. Considering models of technology diffusion, qualitative metrics are required as a result of assigning values to the social features that determine adoption behaviours. These include aspects such as the confidence levels associated with a new technology, or the coefficients of innovation and imitation used in the Bass diffusion model (see chapter 2 for details). Consequently, measurements of adopter perceptions, social influence, and decision criteria are important qualitative aspects to address.

Table 3.5: Data acquisition and modelling strategy

<table>
<tr><th rowspan="2">Main research question</th><th rowspan="2">Supporting question</th><th colspan="2">Data sources</th><th rowspan="2">Models</th></tr>
<tr><th>Qualitative</th><th>Quantitative</th></tr>
<tr><td rowspan="3">What does a technological substitution look like?</td><td>What are the characteristics of technological substitutions?</td><td rowspan="3">• Historic narratives
• National development studies</td><td>• Bibliometrics
• Patent databases
• Market data</td><td>• Technology Life Cycle</td></tr>
<tr><td>How do technological innovations diffuse across large technological systems?</td><td rowspan="2">• Market data
• Economic data
• Technology timelines</td><td rowspan="2">• Agent based models
• System dynamics</td></tr>
<tr><td>What impact do different types of technological substitutions have on adoption dynamics?</td></tr>
<tr><td rowspan="4">To what extent are technological substitution dynamics dependent on scientific foresight?</td><td>How are scientific and technological progress measured?</td><td>• Literature survey
• Technical reports</td><td>• Bibliometrics
• Patent databases</td><td rowspan="2">• Pattern recognition
• Functional data analysis</td></tr>
<tr><td>What are the characteristics of technological anomalies?</td><td rowspan="2">• Historic narratives</td><td>• Bibliometrics
• Patent databases
• Technology timelines</td></tr>
<tr><td>How are technological anomalies and performance stagnation related to technological substitutions?</td><td>• Patent databases
• Market data</td><td rowspan="2">• Agent based models
• System dynamics</td></tr>
<tr><td>How viable are technology substitution models based on data-driven substitution classifications?</td><td>• Structured survey</td><td>• Market data
• Economic data</td></tr>
</table>

Analysis software packages such as NVivo demonstrate some of the capabilities that are currently available for making sense of qualitative data. This includes automation to assist with cataloguing large volumes of narrative data (e.g. searching and extracting themes from grouped batches of PDF documents), and mind-mapping tools. Whilst acting as a powerful means of accelerating analysis and insight when handling complex data sets, as with any tool, these software packages should be used with caution to prevent over-dependency on the automation provided to formulate conclusions. The ability to identify themes in qualitative data sources, classify data into meaningful categories, rank the frequency of occurrence, and the connection to other data repositories (e.g. statistical accounts, live data feeds, etc.) provides a basis for fusing this data with conventional quantitative data sources. This allows intangibles metrics to be assessed in a similar way to tangible metrics. Ultimately though, sophisticated tools available for both qualitative and quantitative data are often limited by the overall availability of data and time required to process it, meaning these factors can also restrict the data and model types that can be considered in practice. There are also risks associated with using commercially sensitive or personal data (which may require anonymisation, encryption, and/or deletion after use), although these can normally be mitigated by using publicly available open data sources. If suitable data sources are found, the dependencies between models also need to be considered, to construct a full picture of where and when data needs to be made available, for the model to function as planned. This assists the identification of any bottlenecks in the modelling procedure. With these considerations in mind, potential data sources for commonly encountered data types are shown in Fig. 3.7, helping to structure the basic data acquisition and modelling strategy, shown in Table 3.5 (discussed in more detail in the next chapter).

3.7 Conclusion

Socio-technical systems present a diverse range of challenges to researchers exploring phenomenon in these environments. This is often due to the plurality of views represented within these systems, and the complex interdependencies existing between technical and social domains. Taking into account the philosophical stance of the author and general hypothesis regarding technology substitutions, problem structuring methods (including Soft System Methodologies and Hierarchical Process Modelling) have been applied to refine the study's research questions and activities. These methods, coupled with a review of data requirements, provide a means to explore the complexity associated with modelling technology substitutions, and enable a meaningful research strategy to be developed to structure the study.

Chapter 4

Modelling approaches and validation techniques

Having outlined the problem definition and research strategy in the previous chapter, the data and methods most applicable for gaining insight into the dynamics of technology substitutions are now considered in more detail in this chapter. To begin with, the selection criteria for the case studies considered in this research is introduced along with a discussion of the general means of gauging technological development. Next, data sources are presented that are considered representative of historically observed technological development efforts, performance improvement trends, and market diffusion patterns. Based on the data available from these historical records, some of the specific concerns that arise when using comparisons of dissimilar time series as a basis for modelling and attempting to reproduce real-world behaviours, are then discussed. Following on from this, typical approaches to deal with time series analysis are presented, and techniques better suited to capturing real-world dynamics. This is followed by an overview of common goodness-of-fit measures that might be used to compare observed and predicted datasets for derived models. The challenges faced when attempting to model or simulate future technology substitutions are then considered in general terms in relation to the receiving audience, along with prevalent themes in the validation of simulated results. Guided by these considerations, relevant techniques are then mapped against the envisaged analysis stages, addressing the research questions posed in chapter 3. Finally, an overview of expected method limitations is provided, although a more detailed review of each stage of the analysis is included in chapters 5 and 6.

4.1 Assessment of technological development

In order to investigate general technology development and diffusion patterns, a range of historical case studies have been examined in this research. In this regard, this study considers 23 technologies, defined in Table 5.2 in chapter 5, where literature evidence has been identified to classify the modes of technology substitution observed. These technologies were selected based on four criteria:

1. Is there a historical narrative available?
2. Is there accompanying (and consistent) performance data available for both the preceding and replacement technologies? (i.e. to provide evidence of the mode of substitution)
3. Do a sufficient number of patent records exist for the replacement technology?
4. Is there accompanying adoption data present for the replacement technology for use in the subsequent technology diffusion studies?

The logic used in this categorisation and supporting evidence is outlined in greater detail in section 2.5 of chapter 2.

A range of possible techniques exist that can be used for gauging the progress of technological development. Correlation analysis and statistical significance testing techniques provide one means of identifying underlying patterns and trends in historical data which may appear, at first, completely dissimilar. This is not to say that statistical analysis provides the only means of identifying underlying patterns in substitution behaviours, as experimental techniques can also provide significant insight into the influences behind observed development and adoption behaviours. However, as technologies can take multiple decades and extensive resources to bring to fruition, trial-and-error approaches are less appealing, although may provide higher quality empirical data to validate hypotheses (i.e. both qualitative and quantitative). Alternatively, features of interest associated with technological substitutions can be identified through a visual inspection of historical data. Yet detection of features in this way is often more haphazard, and likely to be limited by the visual processing abilities of human researchers unless assisted by other analytical techniques. The recognition of measurable features alone is also not sufficient to provide a causal explanation of observed substitution behaviours. For this, more localised hypothesis testing is required to establish directional relationships between specific technological development characteristics and market dynamics. Equally, more qualitative practices based on case studies, surveys, and expert elicitation can also provide valuable insight here, although the consistency associated with these approaches can vary significantly, whilst the techniques themselves do not always scale well to large commercial applications. However, identifying correlations of interest from statistical analysis can help in building hypotheses to test, leading to later causal understanding. In this sense, the statistical analysis presented in chapter 5 provides a systematic basis for the exploration of causal relationships considered in chapter 6.

Bibliometric analysis methods provide a common starting point for many statistical studies of technologies. In recent years bibliometric studies based on patent records have become a well-established means of assessment for both industry market comparisons and government policy setting purposes. Using these techniques it is possible to extract a variety of historical trends for technologies of interest, effectively generating a collection of time series data points associated with a technology (these multidimensional time series datasets are referred to here as *technology profiles*). This raises next the question of how best to compare dissimilar bibliometric technology profiles, in an unbiased manner, to investigate whether literature-based technology substitution groups can be determined using a classification system built on the assumptions in section 2.5. In particular, comparisons of technology time series can be subject to one or more areas of dissimilarity: they may be based on different numbers of observations (e.g. covering different time spans), out of phase with each other, subject to long and short term cyclic trends, at different stages through the TLC (or fluctuating between different stages) [Little, 1981], or be representative of dissimilar industries.

4.2 Selected data sources

Considering the data sources available and the modelling strategy outlined in Fig. 3.7 and Table 3.5 respectively two main types of data sources are considered in this study. In chapter 5, bibliometric sources (in terms of extracted patent datasets) are analysed for the technologies of interest, before being coupled with technology adoption data as part of the technology substitution model developed in chapter 6. Combining these two data sources subsequently enables the impact of different modes of substitution to be related to measured development efforts. These data sources are now considered in greater detail.

4.2.1 Patent data

Patent data is sourced from the Questel-Orbit patent search platform in this analysis. The full FamPat database was considered, which groups related invention-based patents filed in multiple international jurisdictions into 'families' in accordance with EPO's strict family rules[1]. As such invention-based patent families are counted in this analysis, including both applications and granted patents to provide a complete reflection of associated technological development activities (bearing in mind the distinction between scientific production and progress discussed in section 2.6). The data gathered covers all patent offices registered in the FamPat database[2]. Some of the core functionalities behind this search engine are outlined in [Lambert, 2000]. This platform is accessed by subscribers via an online search engine that allows complex patent record searches to be structured, saved, and exported in a variety of formats. A selection of keywords, dates, and classification categories are used in this search engine to build relevant queries for each technology (this process is discussed in more detail in chapter 5). Search terms provided are then matched to the title, abstract, and key content of family records. Unlike title and abstract searches, key content searches (which include independent claims, advantages, drawbacks, and the main patent object) are limited to English language publications.

4.2.2 Technology adoption data

Adoption data for the technologies investigated is taken from a wide variety of sources due to the broad scope of the technology domains considered. Where possible, global technology sales and shipment values have been used to determine the overall market share of each technology at a given time. In some cases, data values have been imputed to fill gaps in time series (this is stated when applicable, along with the method of deriving imputed values). Furthermore, statistical data has been sourced directly from international organisations such as the United Nations, World Bank, International Energy Agency, International Council on Clean Transportation, International Telecommunication Union, and Eurostat

[1] https://www.questel.com/wp-content/uploads/2016/04/FamPat-Rules.pdf
[2] http://static.orbit.com/orbit/help/1.9.6/en/index.html#!Documents/thefampatcollection.htm

Table 4.1: Data sources for technology adoption data

Technology adoption data source	Description
Ascend Fleets	Ascend Fleets, provided by Flight Global, is a subscriber-based online database that stores real-time aircraft and commercial aviation data on both current and historical fleets. This comprises over 240,000 aircraft records, including comprehensive transaction and status data on commercial, business, and helicopter operations [Flight Global, 2017]
BIS Strategic Decisions	BIS Strategic Decisions was the third largest provider of information to vendors in the information technology industry until 1995 when it was acquired by the Giga Information Group. Until this point, BIS Strategic Decisions kept a tracker of the U.S. printer market shipments which were reported annually in 'PC Magazine' (NB: full details of assumptions and imputations during the compilation of observed printer market share values are recorded in Appendix E)
Eurostat	Eurostat is a Directorate-General of the European Commission that provides statistical information to the institutions of the European Union and records historical data for all major forms of transportation in the EU, including details of annual vehicle registrations [Eurostat, 2017]
International Council on Clean Transportation (ICCT)	The ICCT is an independent non-profit organisation that produces the 'European Vehicle Market Statistics pocketbook', which provides an annual summary of the passenger car and light vehicle fleets in the EU, with an emphasis on vehicle technologies and the emission of greenhouse gases and other pollutants [The International Council on Clean Transportation, 2016]
International Data Corporation (IDC)	IDC is a Chinese market research and analysis company that specialises in information technology and publishes an annual hardcopy peripheral tracker charting the historical trends in global printer markets (NB: full details of assumptions and imputations during the compilation of observed printer market share values are recorded in Appendix E) [International Data Corporation]
International Energy Agency (IEA)	The IEA is an intergovernmental organisation established as part of the Organisation for Economic Co-Operation and Development (OECD) in 1974, as a policy advisor to its member and non-member states. It is also an information source on energy statistics. Numerous statistical datasets are available from the IEA, including global energy demand and production, global proliferation of renewable energy technologies, and domestic energy consumption patterns [International Energy Agency, 2016, International Energy Agency 4E, 2014]
International Telecommunications Union (ITU)	The ITU is a specialised agency of the United Nations that is responsible for issues that concern information and communication technologies. It publishes statistics and reports annually on global telecommunications coverage [International Telecommunication Union, 2016]
IT Candor	IT Candor is a market research company working in the IT and Communications industry that produces annual statistics and forecasts for a range of small, medium, and large hardware providers, including trackers of worldwide printer shipments [IT Candor, 2016, IT Candor]
World Bank	The World Bank is an international financial institution that aims to reduce worldwide poverty by promoting foreign investment and international trade. It collects and processes large amounts of data based on economic models, and regularly publishes global development indicators in an open access format [The World Bank, 2016, Harris et al., 2000, The World Bank, 2017]

where available, as this is globally representative, often well-substantiated, and encompasses regional development trends. In many cases, this information was accessed via the UK Data Service [UK Data Service, 2017]. A brief description of each technology adoption data source is given in Table 4.1.

4.3 Statistical comparisons of time series

Having introduced the data sources used in this study to explore patterns of historical technology development and commercialisation, this chapter now considers statistical methods related to the comparison of time series in more detail. An extensive body of work already exists in this field, which includes the comparison of dissimilar time series (such as are provided by the chosen datasets), with particular focus on time series classification methods [Lin et al., 2012]. Most modern time series

Table 4.2: Common time series pattern recognition techniques [Lin et al., 2012]

Supervised learning	Semi-supervised learning	Unsupervised learning
• Memory-based reasoning (e.g. nearest neighbour -- often the standard approach) • Decision trees • Rule induction • Bayesian networks • Support Vector Machines (SVMs) • Neural networks • Linear discriminant analysis	• Self-training algorithms such as semi-supervised 1-NN (nearest neighbour with leave-one-out cross validation) • Efficient combinatorial approach based on Markov chains • Transduction • Time series discords	• Principal Components Analysis (variable reduction procedure) • Hierarchical clustering • K-Means/K-Medoids • Expectation-Maximisation • Canonical Correlation Analysis • Partial Least Squares

pattern recognition and classification techniques emerging from the machine learning and data science domains broadly fall within the categories of supervised, semi-supervised, or unsupervised learning approaches. The distinction between these categories is based on the amount of training information provided to the classifier in each case. In supervised learning, training time series are provided with known classification labels, whilst training time series with both known and unknown classification labels are used in semi-supervised learning. By contrast, unsupervised learning approaches are not provided with any classification labels, and as such are required to determine groupings independently (e.g. clustering) [Lin et al., 2012]. Table 4.2 provides an overview of time series pattern recognition techniques commonly used (this list is not exhaustive).

4.3.1 Preprocessing and statistical significance testing of time series classifications

Beyond the principal methods of classification outlined, the preprocessing of time series datasets and means of statistical significance testing must also be considered. Preprocessing of data is still an area that divides opinion within the statistics community, with some experts arguing that transformation, smoothing, and normalisation of datasets is required for unbiased time series comparisons, whilst others contend that in doing so a lot of information is removed that could otherwise be captured in error terms and that correlations may be over-stated [Lucero and Koenig, 2000, Ramsay et al., 2009, WolframAlpha.com, Researchgate.net, 2013, Stackoverflow.com, 2015b]. If focusing on long-term trends, it is often recommended that analysis is based on either logarithms or inverse hyperbolic sine transformations of time series data rather than raw data to reduce focus on short cyclic features [Ramsay, 2013a, Nau, Hyndman, 2010, Researchgate.net, 2014]. Similarly, simple moving averages are thought to be more appropriate than exponential smoothing (for long term trends if smoothing is to be applied) [Twomey].

A key data preparation requirement in the current study is the definition of shared curve features from bibliometric data that can be used to address the time series and TLC alignment issues highlighted in section 4.3. These feature recognition and alignment processes are required to enable classification based on fair comparisons of dissimilar technologies. To ensure consistency, feature recognition processes should consider the relative height of plateaux between technology profiles from different industries, the rates of growth in the early stages of historical trends, and the influence of noise and incomplete time series data on the classifications made. It is therefore assumed that unsmoothed, amplitude normalised time series which are subsequently segmented based on common curve features would enable these comparisons to be made. This approach ensures that all curve amplitudes are relative on a global scale, whilst segmentation by common features enables consistency in defining early growth phases whilst allowing later incomplete segments to be discarded from classifications. As a basis for these feature extraction stages it is assumed that the TLC model proposed by Little provides a well-established concept and sensible candidate for identification of common curve features [Little, 1981]. However, identified curve features may still be unaligned in time, and consequently time transformation techniques, such as 'time warping' methods, are also recommended (this is discussed in more detail in section 4.3.2).

In terms of being able to determine correlations between groups of time series datasets the Chi-square statistic is commonly used to test the independence of descriptive statistics derived from time series (time series classifiers are discussed in more detail in section 4.3.2). However, as a consequence of the probability distribution function used in its significance test, the Chi-squared approach is best suited to confusion matrices (i.e. cross-tabulated comparisons of predicted classifications against target classifications) which have all cell values greater than or equal to five. As such, when smaller sample sizes are considered (such as the 23 technologies in this analysis), Fisher's exact test is more appropriate. In a similar fashion to the Chi-square test, Fisher's exact test determines the significance of outcomes for samples taken at random from a population, but is not necessarily able to provide a ranking of the most statistically robust predictors (i.e. predictors that are likely to be accurate when considering out-of-sample predictions). It is worth noting that in the current study technologies have been deliberately selected based on their observed performance trends. As such, Fisher's exact test cannot be used to reject the null hypothesis (as samples are not taken at random from a population) unless known time series classification labels are removed to prevent clustering based on human biases (i.e. an unsupervised learning approach).

For subsequent ranking of predictors based on small sample sizes, cross-validation approaches are required (discussed in more detail in section 4.3.5). Histograms can also prove useful for determining the most frequently occurring individual factors in these cross-validation 'bootstrapping' processes, but cannot indicate the combination of factors that work best together.

4.3.2 Time series classification and feature alignment techniques

To identify and rank the predictive ability of different combinations of bibliometric indicators when used for classification purposes, an appropriate classifier first must be selected that fits the data features considered. In this sense, time series classification procedures can be grouped based on the type of discriminatory features they are attempting to find (see Table 4.3 [Bagnall et al., 2016]).

Table 4.3: Types of time series classification techniques [Bagnall et al., 2016]

Method type	Description
Whole series	two time series compared either as a vector or by a distance measure that uses all the data
Intervals	rather than use whole series, select one or more phase dependent intervals of the series
Shapelets	based on finding short, phase independent, patterns (shapelets) that define class, but that can appear anywhere in series. Class is distinguished by presence or absence of one or more shapelets anywhere in whole series
Dictionary based	classification based on histograms constructed from frequency counts of recurring patterns
Combinations	class of algorithms based on combining two or more of the above approaches into a single classifier
Model based	Model based algorithms fit a generative model to each series then measure similarity between series using similarity between models. Commonly proposed for tasks other than classification or as part of a larger classification scheme and are often not as competitive as other approaches (except for long series of unequal length)

Recent benchmarking analysis has found that few time series classification algorithms perform better than the Dynamic Time Warping (DTW) and Rotation Forest benchmark classifiers, whilst the best alternative (COTE) was identified as very computationally expensive [Bagnall et al., 2016]. It is worth noting that feature alignment techniques that calculate relative feature-based distance measures between time series (such as whole series and interval approaches) can be used to calculate single value representations of the similarity between pairs of time series, including complex time series with multiple dimensions, which can subsequently be used in further clustering or wider classification analysis.

In DTW, feature alignment is achieved by stretching portions of two signals, X and Y, onto a shared set of instances such that a global signal-to-signal distance measure is minimised. The set of distortion paths used in this minimisation problem are based on a lattice of all possible distances between the m^{th} data point of X and n^{th} data point of Y (as illustrated in Fig. 4.1).

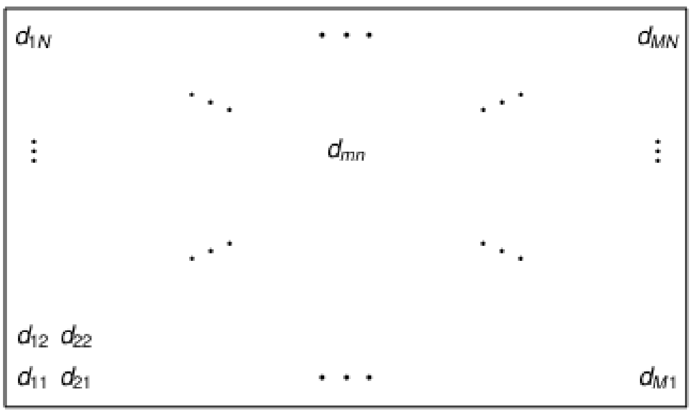


Figure 4.1: Lattice of all possible distances between the m^{th} data point of X and n^{th} data point of Y [MathWorks, 2016a]

Valid warping paths, parameterised by two sequences of the same length, are a combination of "chess king" moves which completely aligns the signals, and does not skip any data points or repeat any signal features (illustrated in Fig. 4.2).

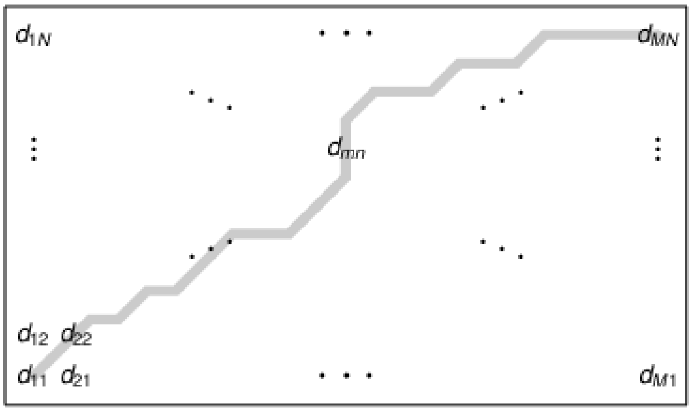


Figure 4.2: Valid warping path that completely aligns two signals [MathWorks, 2016a]

To determine the minimum warping path the algorithm forces similar features to appear at the same location on a common time axis [MathWorks, 2016a]. This is demonstrated in Fig. 4.3 and Fig. 4.4 for one-dimensional and multidimensional signals respectively, where in both cases two misaligned input signals are distorted to enable signal alignment to take place. Fig. 4.3 shows this in a one-dimensional example where individual signal values are repeated within each input signal vector to locally stretch portions of both signals in the x-direction. In doing so, the algorithm counts the number of inserted elements for each input signal based on the current distortion paths and uses this to compute the distance required to align the signals. This solution can then be tested against other possible distortion paths to determine the minimum amount of distortion needed. The same principle is then applied for the ten-dimensional signal shown in Fig. 4.4 (with dimensions shown as different 'layers' on the y-axis, and rescaled time values on the x-axis), but in this case any distortions made are carried across all 10 dimensions. The undistorted input signals are shown in the two top left images shown in Fig. 4.4 , with the original overlay of these two signals shown in the bottom left image. The equivalent realigned signals are then shown on the right hand side of Fig. 4.4.

4.3.3 Time series clustering techniques

As a form of unsupervised learning, clustering approaches enable associations between time series to be identified without being subjected to human grouping biases. However, to apply clustering techniques it is necessary to describe the relationships between successive pairs of time series using single value representations. Consequently, time series clustering techniques tend to be based on measures of the relative distance between curves, rather than the curve data points themselves. The outcomes also vary considerably depending on the clustering algorithm selected. This includes the real-world interpretation of the groupings generated, as observed when comparing clusters predicted using the K-means and K-medoids algorithms. Fig. 4.5 illustrates how the centre of subsets in K-means is equivalent to the mean

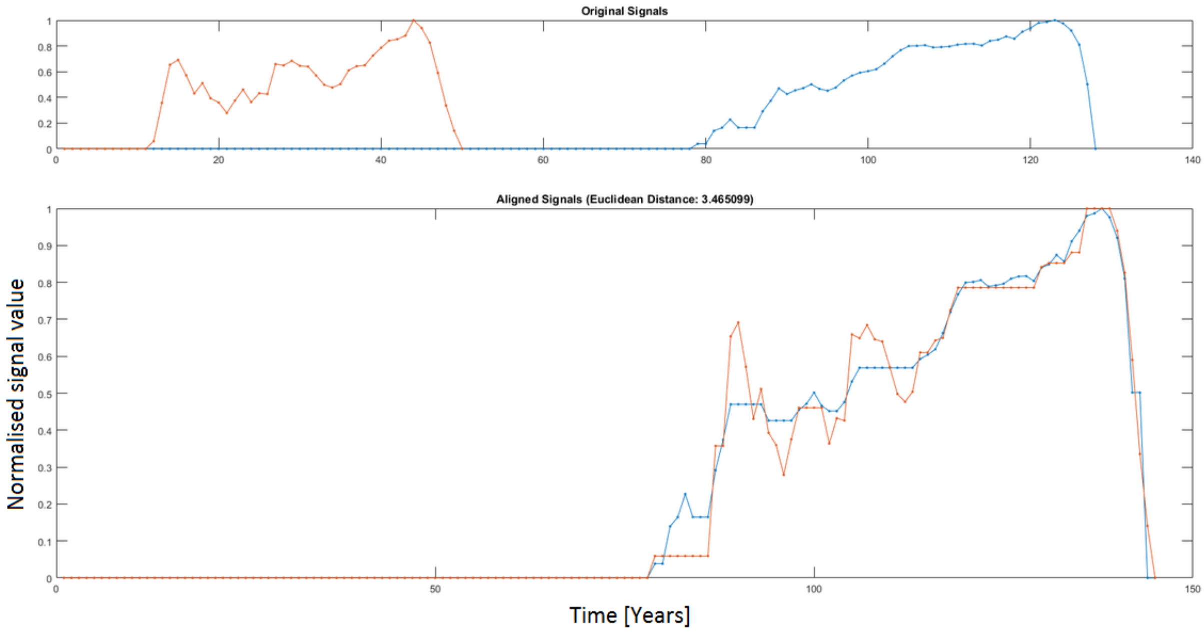


Figure 4.3: Example of feature alignment and Euclidean distance measurement using Dynamic Time Warping on unaligned signals

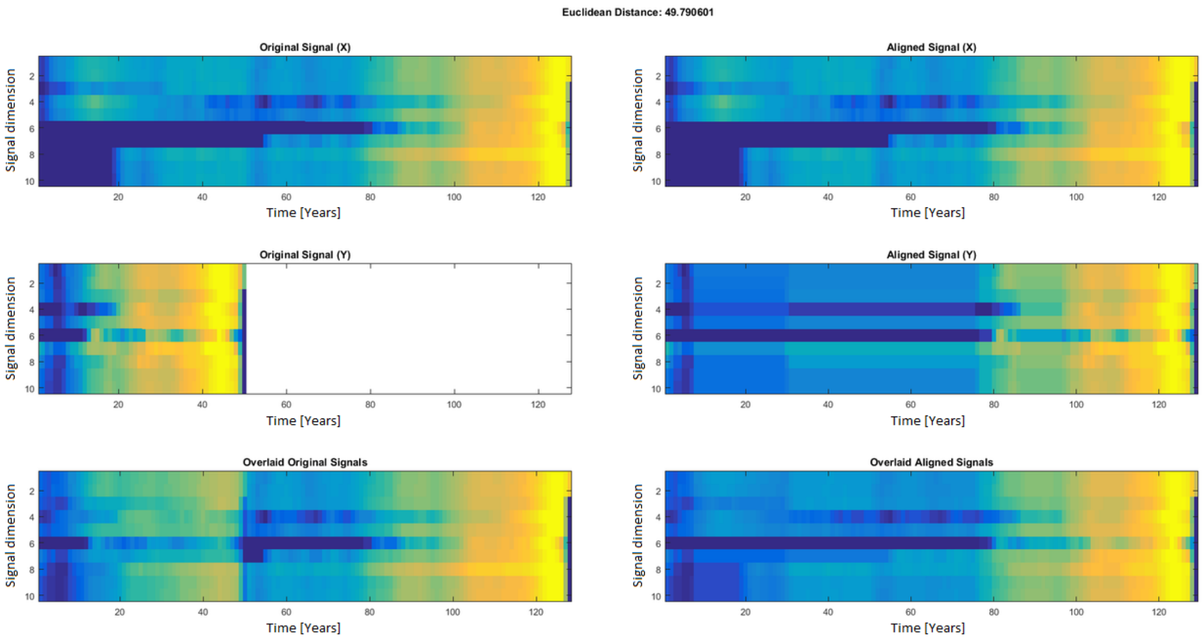


Figure 4.4: Example of feature alignment and Euclidean distance measurement using DTW on unaligned multi-dimensional signals

of measurements in the subset (the centroid), rather than an actual member of the subset (a medoid). Therefore, K-means is not appropriate for application to time series, as the algorithm minimises variance, rather than distances, between curves [MathWorks, 2016b, Stackoverflow.com, 2015a]. In this particular instance, where distances between technology development curves are being considered, each subset member would correspond to a specific technology, positioned based on the distance measures provided by DTW relative to the other technologies considered. Since the centroid of a set of data points does not typically coincide with a real observation, the centroid in this scenario therefore corresponds to a non-existent mean technology with minimum variance from the other technologies in the same subset. This is distinct from identifying the technology present in the current subset that is most characteristic of the labelled substitution mode.

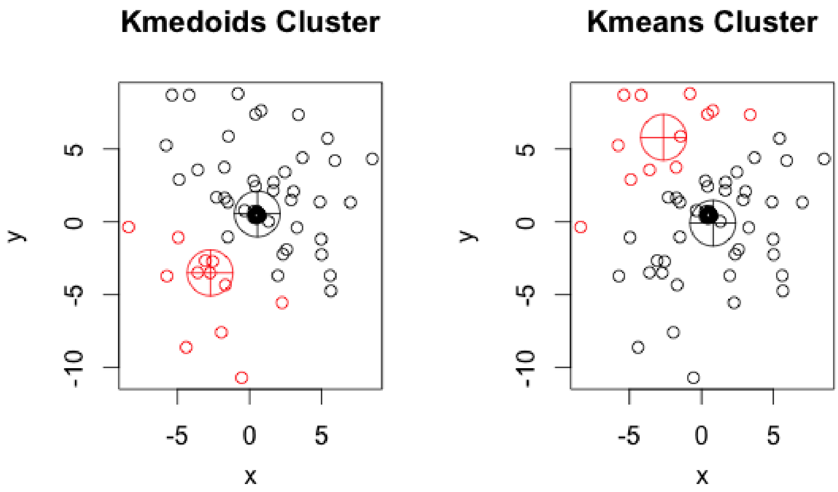


Figure 4.5: Differences in real-world interpretations of K-means and K-medoids clustering algorithms

Besides predicting alternative central points for subsets and grouping alternative subset members, the number of clusters predicted can also vary depending on the algorithm selected. Whereas K-means and K-medoids require the number of clusters to be specified in advance, hierarchical clustering approaches automatically determine the number of clusters to group data points into without additional human intervention [MathWorks, 2016b, Stackoverflow.com, 2015a]. Furthermore, as a form of unsupervised learning, clustering approaches provide different group labels to subsets each time they are applied, even if the actual subset members remain unchanged. Therefore, a separate 'subset mapping' function based on 'Hamming distance' is required to ensure consistency in comparisons between generated clusters and expected groupings (defined in Table 4.4). Again, it is worth noting that the definition of subsets using any clustering technique is only valid if time series are compared on comparative features, rather than incomplete time series data. As such, time series segmentation based on shared features or imputation of missing data is again a prerequisite for meaningful analysis, ensuring that only completed segments are used in defining subsets. Finally, if using feature-based distance measures as the basis for clustering (grouped into matrices of distance points relating each technology time series to every other time series), it is suggested that either hierarchical clustering or the 'Partitioning Around Medoids' (PAM) variant of K-Medoids are applied to the descriptive data [MathWorks, 2016b, Stackoverflow.com, 2015a].

4.3.4 Distance measures used in clustering and feature alignment

A range of distance measures can be used as the basis of clustering and feature alignment techniques, each with their own specific focus when comparing data points. Some of the most commonly encountered distance metrics are summarised in Table 4.4 [Math.NET, MathWorks]. Of these, the

Table 4.4: Distance measures that can be used in clustering and feature alignment

Metric	Description
Euclidean distance	The straight-line distance between two points in Euclidean space
Squared Euclidean distance	Squared Euclidean distance uses the same equation as the Euclidean distance, except that it does not take the square root. This results in an improved efficiency for Jarvis-Patrick and K-Means clustering without affecting the output. However, the output of hierarchical clustering is likely to change
Normalised Euclidean distance	Provides the Squared Euclidean distance between two vectors where the vector lengths have been scaled to be of unit length. This is useful when the direction of the vectors is meaningful but the magnitude is not
Manhattan distance	The distance between two points is measured as the sum of the absolute differences of their Cartesian coordinates (also known as the taxicab, rectilinear, or City block distance)
Minkowski distance	Defines a distance between two points in a normed vector space, which can be considered as a generalisation of both the Euclidean and Manhattan distances
Chebychev distance	The distance between two vectors represented by the greatest of their differences along any coordinate dimension (i.e. maximum coordinate difference, equivalent to the minimum number of moves required for a King in the game of Chess to move from one square to any other)
Mahalanobis distance	A distance metric that accounts for the variance of each variable and the covariance between variables, whilst taking into account the scale of the data. This is equivalent geometrically to transforming the data into normalised uncorrelated data and computing the ordinary Euclidean distance for the transformed data
Cosine distance	The cosine distance represents the angular distance of two vectors while ignoring their scale, and is defined as one minus the cosine of the included angle between points (treated as vectors)
Pearson distance	The Pearson distance is a correlation distance based on Pearson's product-momentum correlation coefficient of the two sample vectors. Since the correlation coefficient falls between [-1, 1], the Pearson distance lies in [0, 2] and measures the linear relationship between the two vectors
Spearman distance	The correlation between two sequences of values. The two sequences are ranked separately and the differences in rank are calculated at each position. Calculated as one minus the sample Spearman's rank correlation between observations
Hamming distance	The percentage of coordinates that differ
Jaccard distance	One minus the Jaccard coefficient, which is the percentage of non-zero coordinates that differ

Euclidean distance is normally the default for most clustering software. However, the choice of distance metric is very important, as it often has a strong influence on the results of any clustering. Distance metrics may refer to a standard measurement of differences between points in either Cartesian or transformed coordinate systems, the percentage dissimilarity between coordinate values, or correlation observed between vectors. The choice of distance metric ultimately depends on the type of data and research questions being addressed. For example, if seeking to identify clusters based on the similarity of profiles regardless of their magnitudes, correlation-based distances are normally better suited as a dissimilarity measure, as these consider the similarity of features irrespective of the Euclidean distance [Kassambara]. However, Euclidean-based distance measures can be equally appropriate for gauging the similarity of time series, if normalisation of the original time series has taken place [Berthold and Höppner, 2016].

Table 4.5: Common cross-validation techniques

Exhaustive cross-validation approaches	Non-exhaustive cross-validation approaches
• Leave-p-out cross-validation • Leave-one-out cross-validation (most computationally inexpensive version of leave-p-out cross-validation)	• k-fold cross-validation • Holdout method • Monte Carlo (repeated random sub-sampling)

4.3.5 Cross-validation techniques

To assess the predictive performance of any given combination of bibliometric indicators in practice, it is necessary to determine how the classification results will generalise to an independent (i.e. unknown) data set. For this purpose, cross-validation techniques are commonly employed to provide an indication of model validity when considering out-of-sample predictions. This is accomplished by sequentially training and then generating test predictions from different subset decompositions of the original data, and using the average number of misclassified observations to rank each predictor grouping. In doing so, cross-validation helps to address the risk of over-fitting models that are based on limited sample sizes, but equally provides a means to identify the most suitable predictor groupings to use for model building purposes, based on their robustness to misclassifications. Cross-validation techniques are generally grouped into either exhaustive or non-exhaustive categories, as in Table 4.5.

Some known limitations should be taken into consideration when applying cross-validation techniques. In particular, cross-validation approaches only yield meaningful results if the validation and training sets are drawn from the same population (without overlap between sets), and if human biases are controlled. It is unrealistic to treat data as being drawn from the same population when using dissimilar time periods for validation and training sets, as the shift in time introduces systematic differences into these sets. As such, alignment of features to ensure consistency is again advisable for fair comparisons of time series. Similarly, training models based on a specific group within a population (e.g. young people) does not enable generalisation of cross-validated training results to the wider population, as predictions could differ greatly to actual results.

4.3.6 Functional data analysis

Most statistical analysis techniques assume that the data points being evaluated are unrelated, and can be treated as independent entities. This is not generally true of time series, where there is often a derivative function that connects adjoining data points together. To address this, functional data analysis approaches were developed to enable statistical analysis and model construction based on whole functions, rather than a collection of independent data points, making these approaches preferable for time series data [Ramsay et al., 2009]. Additionally, functional data analytics is suitable for conditions where data contains phase variations (such as in growth data and historical trends where curves start at different times/stages). Methods such as non-linear mixed models, repeated measure

ANOVA, and principal components analysis do not consider these differences in timing [Stackoverflow.com, 2012].

Functional data approaches are built on the principle of using linear expansion of *basis functions* to represent data series as a *functional data object* [Ramsay et al., 2009]. *Basis function expansions* are defined by:

$$f\left(t\right)=\sum_{k=1}^{K}\beta_k\theta_k\left(t\right) \tag{4.1}$$

where $\theta_k\left(t\right)$ are known *basis functions*, and β_k are the estimated coefficients associated with these basis functions. This is often also written as:

$$f\left(t\right)=a_1\theta_1\left(t\right)+a_2\theta_2\left(t\right)+...+a_k\theta_k\left(t\right) \tag{4.2}$$

Accordingly, functional data objects are built by adding the scaled series of basis function terms together to create a single function. Functional data objects can subsequently be used in functional linear regression analysis, analogous to conventional linear regression:

$$y=X\beta+\varepsilon \tag{4.3}$$

where

$$y=\begin{pmatrix}y_1\\y_2\\\vdots\\y_n\end{pmatrix},X=\begin{pmatrix}x_1^T\\x_2^T\\\vdots\\x_n^T\end{pmatrix}=\left(\begin{bmatrix}x_{11}\cdots x_{1p}\\x_{21}\cdots x_{2p}\\\vdots\ddots\vdots\\x_{n1}\cdots x_{np}\end{bmatrix}\right),\beta=\begin{pmatrix}\beta_1\\\beta_2\\\vdots\\\beta_p\end{pmatrix},\varepsilon=\begin{pmatrix}\varepsilon_1\\\varepsilon_2\\\vdots\\\varepsilon_n\end{pmatrix}$$

A range of different basis systems are available to define basis functions used in functional data objects, with the exact definition of these functions depending on the type of data or feature that functional data objects are replicating. The simplest of these use constant or monomial basis systems. Whilst the utility of constructions in this form are limited for more complex applications, these simple basis systems often provide a useful baseline for comparison in benchmarking analysis.

At their most basic level, Fourier series are commonly used for periodic and near periodic data (such as for weather data and some economic data), whilst spline-based functions are used for non-periodic data [Ramsay et al., 2009]. Beyond these, higher level distinctions, polynomial, B-spline (which are essentially built from many polynomial sections), and wavelet functions can also be considered. B-splines fit highly curvy data well, without requiring the large number of basis functions polynomials need to achieve the same fit. Consequently, splines have now largely replaced polynomials. An illustration of how a typical B-spline basis system might appear (in this case with 54 basis functions) is shown in Fig. 4.6, whilst an example of how curve fits are achieved through the scaling of individual basis functions within such a basis system is shown in Fig. 4.7.

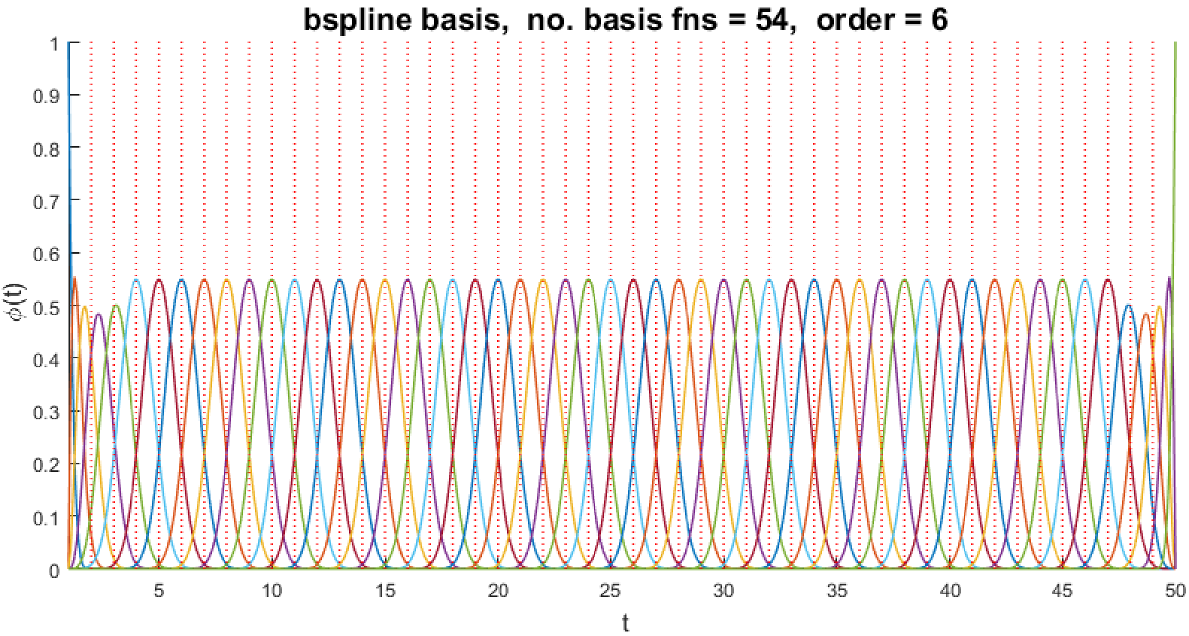


Figure 4.6: Illustration of a typical b-spline basis system, made up of 54 basis functions

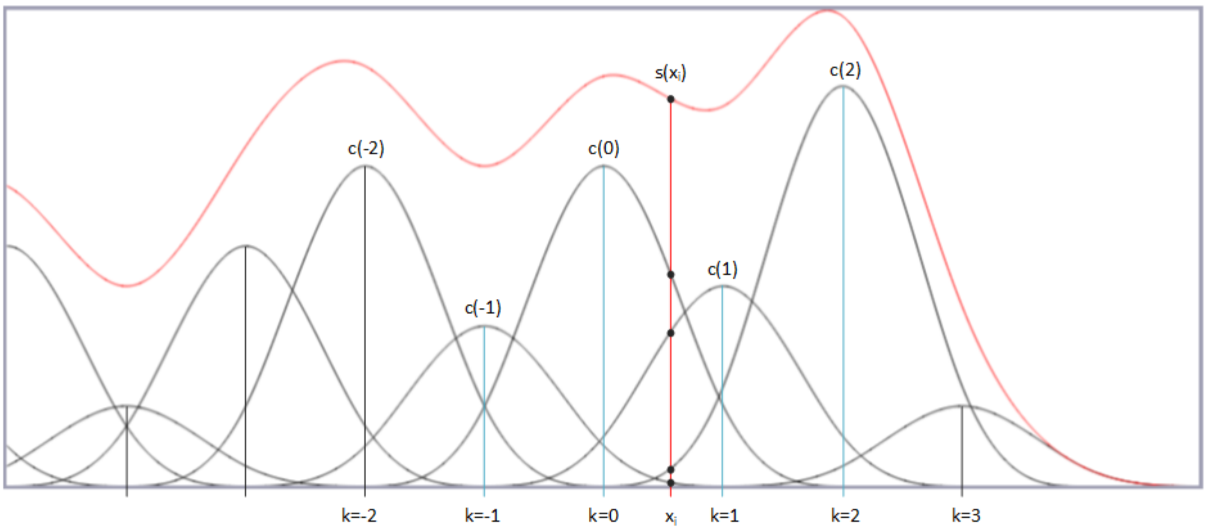


Figure 4.7: Example of b-spline basis system scaling to achieve a curve fit [Shulga, 2014]

Wavelets perform best for capturing sharp edges, which is a particular weakness of Fourier based functions [Ramsay et al., 2009]. If using B-splines, it is necessary to first define the number of *knots* to use in the representation of a curve (i.e. the joining points, or interior boundaries, linking adjacent polynomial segments in the spline). More knots are required for higher order basis functions, as the number of coefficients required to define polynomial segments (the *order*) is always one more than the highest power defining the polynomial (the *degree*). For example, setting the number of knots equivalent to the total number of observations in a time series (i.e. one more than the number of intervals considered) means two coefficients are required to define each polynomial segment, which in this case limits spline sections to straight lines (i.e. of degree one). From this the degrees of freedom associated with a B-spline are equivalent to the sum of the number of interior breakpoints plus the order of the polynomial segments used.

Recommendations of implementation practices for functional data analysis have been presented in the work of Ramsay that should be considered when applying these techniques. Firstly, it is advised that the order of B-spline functions be at least four orders of magnitude larger than the highest order derivative considered in any analysis, to properly capture any significant influences from derivative behaviours [Ramsay et al., 2009]. There is also a need to scale time vectors appropriately so that the time period of each basis function is not significantly less than 1, otherwise rounding errors may occur when large numbers of basis functions are used [Ramsay et al., 2009]. Furthermore, to ensure that a consistent number of observations is used across compared technologies, the analysis that follows assumes that the resampling of time series, based on simple linear interpolation, will not introduce significant errors into the assessment of the predictive ability of different bibliometric indicator groups. Meanwhile, the work of Ramsay provides well-documented evidence from prior studies of how feature alignment processes (also termed 'landmark registration') often form a prerequisite to model building using functional data approaches. As such, time series segmented and aligned based on features, such as aligning technologies against common TLC stages, enable a single data object to be generated for multiple curves that originally spanned different time periods [Ramsay et al., 2009]. Lastly, in applying functional data analysis techniques to other growth curves (such as the U.S. Nondurable Goods Index), Ramsay advocates the use of data transformation and smoothing to focus on long-term trends rather than periodic or seasonal patterns [Ramsay, 2013a,b].

4.4 Modelling real-world behaviours

As discussed later in section 4.6.2, reproducing real-world behaviours in computer-generated models and simulations is challenging. A particular challenge in this study is the representation of technological anomalies generated by functional-failure. Whilst the definition of technological failure in chapter 2 is intended to enable the systematic detection and comparison of such instances, in reality it is very difficult to robustly measure the frequency of events associated with such anomalies. This is due to the fact that no standardised catalogue of historical substitutions exists that provides details of performance development trends required to identify regions of temporary functional-failure, at least not to the extent necessary to confidently determine the frequency of anomaly occurrence for a particular industry. This may be because the performance evidence is either commercially sensitive, or has not been compiled chronologically for competing product ranges into a single consistent time series. Typically, many divergent narratives may be found for technological progress, and performance improvements often appear in an ad-hoc fashion in historical accounts. This makes it difficult to measure the frequency of these type of events for the wide spread of technologies necessary to generate a tailored model of functional-failure anomaly and behaviours. The best that can be done in these circumstances is to assume a more generalised distribution of events associated with these anomalies. Such models commonly include the use of binomial, Gaussian, normal, and Poisson distributions amongst others. Of these, Poisson is potentially the most relevant here as it is suited to predicting discrete counts of events (non-negative) in a given time period [Lamar, Grace-Martin, healthknowledge.org.uk]. These events may represent the increase in everyday challenges observed that are linked to a given scientific constraint, or an increase in awareness of obstacles to continued performance improvement. In this manner it is possible that these events will begin to accumulate or become more frequent as a technology evolves, or as that technology becomes more widely used. Consequently, events associated with functional-failure anomalies can be treated as analogous to modelling conventional failure events in maintenance and reliability analysis of products and systems, by using a Poisson distribution to predict the haphazard nature of occurrence. Equally, Poisson distributions are commonly used to represent the random accumulation of citations over time, as noted by Mingers [Mingers and Leydesdorff, 2015]. As such, representations of functional-failure could adopt a similar strategy, whilst being calibrated to technological case studies using conventional Poisson distribution control parameters (i.e. by defining the mean expected value, skewness, and translational shifts applied to the basic distribution).

Considering the behavioural challenges presented by technology substitution in more general terms, some of the more promising simulation techniques developed to improve representations of real-world dynamics are now introduced.

4.4.1 Agent-Based Modelling

Excluding environmental phenomena, the emergent complexity frequently observed in real-world dynamics often stems from the autonomous nature of the individuals, communities, and organisational entities that make up human societies. These distinct entities, whether individuals or group-based, operate guided by their own values, beliefs, and decision-making capabilities, with varying levels of independence from any centralised governing authorities present. Conventionally, many models of society assume that individuals and organisations behave in a greedy fashion [Medema, 2009]. However, there are many examples where, despite the lack of any centralised authority, real-world entities remain largely regulated in their behaviour (e.g. observed global ATS cooperation), contrary to what might be expected when combining multiple greedy entities. Such examples show that in reality, individual and group-based entities demonstrate reactive, pro-active, cooperative, and social traits. Building on these observed behaviours, Agent-Based Modelling (ABM) is one of the few methods available to explore this level of dynamic and stochastic complexity, by directly considering the interaction of human-centric traits within a modelled group of entities. Several fundamental features are commonly agreed as characteristics of agents, as summarised in Table 4.6 [Macal and North, 2006]. Of these, the most critical condition is that any agent should be capable of making independent decisions, ensuring active, rather than passive, behavioural characteristics.

As ABM is dependent on the interactions between agents and the behaviours that individual agents exhibit, analogies with social and dynamic network analysis (topology) techniques can be made [Macal and North, 2006]. Recent developments in Dynamic Network Analysis (DNA) have enabled the modelling of growth and reshaping of networks based on agent interaction processes [Macal and North, 2006]. In parallel, advances in understanding of human learning processes have allowed ABM to

Table 4.6: Characteristics of agents [Macal and North, 2006]

Trait	Description
A	Agents are identifiable, discrete individuals with a set of characteristics and rules governing its behaviours and decision-making capability. Agents are self-contained
B	Agents are capable of making independent decisions
C	An agent is situated, living in an environment with which it interacts along with other agents. Agents have protocols for interaction with other agents, such as for communication, and the capability to respond to the environment. Agents have the ability to recognise and distinguish the traits of other agents
D	An agent may be goal-directed, having goals to achieve (not necessarily objectives to maximise) with respect to its behaviours. This allows an agent to compare the outcome of its behaviour relative to its goals
E	Agents are autonomous and self-directed. Agents function independently in the environment and their dealings with other agents, at least for range of situations that are of interest
F	Agents are flexible, having the ability to learn and adapt behaviours based on experience. This requires some form of memory. Agents may have rules that modify behavioural rules

replicate more realistic learning behaviours using neural networks, evolutionary and genetic algorithms, and other reinforcement learning techniques [Macal and North, 2006]. Reinforcement learning techniques, such as stochastic learning automata, can be combined with game theory to design adaptive agents that adjust their future actions based on feedback from their environment and the results of competitions [Macal and North, 2006, Zhao and DeLaurentis, 2008, Borrill and Tesfatsion, 2010]. In economic models of competitive market environments, this has led to behavioural trends resembling foresight in agents [Tesauro and Kephart, 2000]. ABM therefore presents a powerful means of simulating some of the complex dynamics observed in real life.

Whilst there was initially considerable scepticism about the value of results published based on ABM, the diverse range of applications means ABM publications are now usually considered methodologically sound. Nevertheless, verification of results remains a crucial test of ABM's effectiveness. In many cases, verification has been difficult to conclusively prove or disprove, especially when simulating hypothetical conditions, or recreating conditions that may be subject to abductive fallacies [Lorenz, 2009]. In most current applications, the verification of ABM rests on the technology beneath the modelling (as this is where it can be most easily challenged), and demonstrating that individual macroscopic behaviours are plausible in one-to-one interactions. If the technology is well-built (i.e. well-coded), then the methodology and epistemology produce more scientifically respected conclusions. However, a considerable amount of time still needs to be designated to the documentation, programmatic testing, and evaluation of case studies and scenarios before formal results from ABM can be published.

4.4.2 Causal Loop Diagrams and System Dynamics

Causal Loop Diagrams (CLDs) and System Dynamics are acknowledged methods for exploring dynamic behaviours in evolving systems when it is unnecessary to incorporate emergent influences [Lorenz, 2009]. They provide a powerful tool for recognising structures (i.e. feedback loops and influences) in nonlinear systems from simple examinations of model structures. CLDs in particular can enable the translation of qualitative statements (as found in historical descriptions or policy statements) into conceptual models related to mathematical expressions of quantitative attributes. This therefore sits between softer interpretivist methodologies and harder functionalist approaches. Additionally, the visual construction of CLDs provides an intuitive way to generate mathematical descriptions of complex phenomenon through stocks (also known as 'levels'), flows, and rates as partial derivatives in the system, without the need for detailed mathematical understanding (making it accessible to audiences from all disciplines). The system dynamics modelling process is described very well in the work of Sterman [Sterman, 2000], illustrating how dynamic hypotheses can be formulated and tested.

CLDs and system dynamics enable numerous soft stocks (often intangible or qualitative values) to be incorporated directly into the structure of the model, alongside more clearly defined metrics. In this manner, system dynamics assists with determining the susceptibility of measured parameters to a range of connected influences not always associated with quantitative metrics. Soft stocks such as 'confidence' cannot be easily built into other modelling constructs without the assistance of CLDs and system dynamics [Fowler, 2003]. However, it is possible to use system dynamics with ABM to ensure that behavioural rules assigned to agents at the microscopic level are consistent with global behavioural dynamics. In contrast to ABM, the implicit link between system dynamics and partial derivatives enables dimensional verification of units and measurements applied in conceptual models. This provides an additional check on the rationality of proposed models, and the capability to identify the dimensionality of new parameters not conventionally modelled. In practical terms, this method can therefore provide triangulation of conceptual models generated by other methodologies, to improve the robustness of the research. There are limitations to this methodology, which principally relate to the modelling of emergent properties, and general restrictions to applications at a macroscopic level due to the deterministic nature of the underlying calculations (see [Borshchev and Filippov, 2004]). However, care should be taken to ensure that data is used to build system dynamics models rather than just the application of "judgement", otherwise the rigour behind the method is lost and conclusions generated are open to scrutiny [Jackson, 2003]. In this regard, the formulation of CLDs based on established historical models, data, and existing academic findings is advisable for verification and validation, prior to extension to new phenomenon.

Table 4.7: Goodness-of-fit, summary statistic, and optimisation control measures

Measure	Formula	Description	Interpretation
Correlation coefficient (r)	$r = \dfrac{n\sum A_tF_t - \sum A_t \sum F_t}{\sqrt{(n\sum A_t^2 - (\sum A_t)^2)(n\sum F_t^2 - (\sum F_t)^2)}}$	A measure of the linear correlation between two variables defined on a scale between +1 and -1	1 = total positive linear correlation, 0 = no linear correlation, -1 = total negative linear correlation
Coefficient of determination (R^2)	$R^2 = r^2$	The proportion of the variance in the dependent variable that is predictable from the independent variable(s)	Measures how well regression line approximates real data points. R^2 of 1 indicates regression line perfectly fits data. Values outside the range 0 to 1 can occur where it is used to measure agreement between observed and modelled values, where modelled values are not obtained by linear regression. R^2 will never decrease as variables are added and will probably increase purely due to chance
Adjusted R^2	$\bar{R}^2 = R^2 - (1 - R^2)\dfrac{p}{n-p-1}$	The proportion of the variance in the dependent variable that is predictable from the independent variable(s), penalised by the number of explanatory variables (not including constants) in the model (p), relative to the sample size (n)	Value will always be less than or equal to R^2. Increases in $\bar{R}^2$ only occur when the increase in R^2 due to including a new variable is more than would be expected as a result of chance
Mean Squared Error (MSE)	$\text{MSE} = \dfrac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}$	A measure of the quality of a predictor, MSE measures the average of the squares of the errors or deviations (units of measurement equal to the square of quantity being predicted). MSE incorporates both the variance of the predictor and its bias. MSE is always non-negative	Values closer to zero are better. Divergence from 0 occurs because of randomness or because predictor does not account for information that could enable a more accurate prediction. An MSE of 0 (typically not possible) indicates estimator predicts observations with perfect accuracy. Often used as relative score for comparative purposes between models
Root Mean Square Error (RMSE)	$\text{RMSE} = \sqrt{\dfrac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}}$	RMSE is the standard deviation of the differences between predicted and observed values in the sample (same units as the quantity being predicted). Equivalent to the square root of the average of squared errors, so describes variation in errors, and not the average error	RMSE is a measure of accuracy, to compare forecasting errors of different models for the same dataset (smaller values better) and not between datasets, as it is scale-dependent. Larger errors have a disproportionately large effect on RMSE
Mean Absolute Error (MAE)	$\text{MAE} = \dfrac{\sum_{t=1}^{n}\lvert A_t - F_t\rvert}{n}$	A measure of the average absolute difference between two continuous variables	A larger average absolute difference implies larger errors throughout the sample, and hence worse accuracy
Mean Absolute Percentage Error (MAPE)	$\text{MAPE} = \dfrac{100}{n}\sum_{t=1}^{n}\left\lvert\dfrac{A_t - F_t}{A_t}\right\rvert$	A measure of prediction accuracy often used in trend forecasts, expressing accuracy as a percentage. Absolute error values are summed for every forecasted point in time and divided by the number of fitted points, n	Smaller values considered better, however a) measure cannot be used if there are zero values (divide by zero error), b) for forecasts which are too low the percentage error cannot exceed 100%, c) for forecasts which are too high there is no upper limit to the percentage error, and d) when comparing models MAPE is biased in that it systematically selects forecasts that are too low
Mean Absolute Scaled Error (MASE)	$\text{MASE} = \dfrac{\sum_{t=1}^{T}\lvert A_t - F_t\rvert}{\frac{T}{T-1}\sum_{t=2}^{T}\lvert A_t - A_{t-1}\rvert}$ (for non-seasonal time series)	A measure of forecast accuracy based on the ratio of the mean absolute error for a given period to the mean absolute error produced by a naive forecast based on the previous period	MASE >1 implies that the actual forecast does worse out of sample than a naive forecast did in sample, in terms of mean absolute error. This suggests that the actual forecast should be discarded in favour of a naive forecast if out-of-sample data is expected to be similar to in-sample data
Integral Squared Error (ISE)	$\text{ISE} = \int (A_t - F_t)^2\, dt$	A simulation control measure (used in optimisations) based on the integral of the square of the error over time	Minimising ISE tends to eliminate large errors quickly, but allows small errors to persist for a long period of time. Often this leads to fast convergence, but with considerable, low amplitude, oscillation
Integral Absolute Error (IAE)	$\text{IAE} = \int \lvert(A_t - F_t)\rvert dt$	A simulation control measure (used in optimisations) based on the integral of the absolute error over time	Minimising IAE results in slower convergence than ISE, but usually with less sustained oscillation
Integral Time-Weighted Absolute Error (ITAE)	$\text{ITAE} = \int t\lvert(A_t - F_t)\rvert dt$	A simulation control measure (used in optimisations) based on the integral of the time-weighted absolute error over time (i.e. weights errors that have existed for a long time more heavily than early errors)	Minimising ITAE results in faster convergence than ISE or IAE following a slow initial response

4.5 Goodness-of-fit, summary statistics, and optimisation control measures for comparing observed and simulated behaviours

To demonstrate methodological rigour, it is necessary to examine 'goodness-of-fit' measures when testing hypotheses through modelling or simulation. These measures describe how well the current model fits a set of observations, typically by considering the discrepancies between observed and predicted values (i.e. residuals), providing an indication of how well the model will predict a future set of observations. Strong performance of goodness-of-fit measures does not guarantee that a model is foolproof, bearing in mind George Box's apt conclusion that *"All models are wrong, but some are useful"*, but suggests that the assumptions are close enough that the model can be considered useful in practice. In reality, the model is almost always false as it is impossible to perfectly realise all assumptions made for one or more reasons. As such, goodness-of-fit measures must be considered in the context of the hypothesis being examined, to determine how close these measures should be to the ideal formulation to demonstrate a robust model for practical applications. For example, if the purpose of the model is prediction, it may not be too important which independent variables are included as long as the fit appears reasonable. If the model is to examine which variables should be included in the structure in the first place, the fit may be less important if the behaviours match expectations. This means that there is no perfect goodness-of-fit measure. However, a range of measures have been established to address different perspectives on a model's fit to real-world observations, which can be used to explore the practicality of the model. Several commonly used goodness-of-fit, summary statistic, and optimisation control measures are presented in Table 4.7 that are useful when considering time series, as demonstrated in the works of Sterman and Oliva [Sterman, 1984, Oliva, 1995, Postlethwaite]. A_t and F_t refer here to the actual and forecast values at time t respectively.

4.6 Challenges when using modelling and simulations in forecasting

Forecasts of prospective market conditions are commonly used in commerce and policy-making, increasingly based on computer-generated simulations of the world, to provide guidance on the implications of possible future scenarios. The acceptance of conclusions produced in this inherently speculative manner can vary greatly based on the evidence provided and target audience concerned, particularly in the case of disruptive findings. Whilst computer-generated visions of the future are now in many different industries [Government Digital Service, 2013b, Airbus S.A.S, 2013, International Monetary Fund, April 2014, IBM, July 2013, Duranton and Turner, 2012], and it has been argued that these may be capable of replicating human behaviours (as illustrated in chapter 2), the professed usefulness varies greatly. Simulated models of human decision-making may anticipate the success or failure of strategic commercial ventures, and are gradually incorporating more in-depth socio-economic analysis in their functionality. Applying more sophisticated computational techniques, which may use complex numerical simulation and qualitative human-factors to approximate real-world influences, leads to increased questions of the validity of the forecasting assumptions being made and the ultimate credibility of predictions created. This is particularly true in instances where large disruptive changes are presented in conclusions [Government Digital Service, 2013a], such as may be found in technology substitutions.

The use of computational methods can be prohibitive to audiences in comparison to other more transparent forecasting approaches (such as industry surveys or expert reasoning) due to the complexity of these techniques. The need for skilled software developers and operators to generate these simulations leads to increased methodological uncertainties, necessitating lengthy calibration processes to ensure a customer-endorsed level of credibility is achieved. This often requires significant development periods and computational expense. To address this increased complexity, forecasters may attempt to expose the presence of uncertainties in their methods, demonstrate the robustness of software platforms, or provide evidence of the elimination of human errors from procedures, amongst many other validation approaches used in reporting findings. Cross-checking simulations against alternative methods, replicating historical data as a benchmark of performance, and providing clarifications of conclusions are common practice to rationalise findings, although the extent to which these are used varies. To understand which forecast features are most critical for demonstrating the credibility and validity of computer-generated predictions (with emphasis on the acceptance of simulated technological disruptions), a systematic review is presented in this section, identifying common factors that emerge from existing literature on simulation methodologies and virtual models of disruptions. These factors are mapped against two specific simulation techniques often used to predict disruptions: agent-based modelling and system dynamics (introduced in section 4.4). Subsequently, the relevance of each theme is assessed for a sample audience from industry, academia, and the commercial sectors, via a structured survey to gauge the most effective means of demonstrating forecast credibility.

4.6.1 Research strategy for identifying and ranking validation themes

To identify and rank commonly occurring validation themes in accounts of modelling and simulation, both qualitative and quantitative methods are applied here to gauge the extent to which different validation methods build credibility in forecasts. A combined approach is better-suited for the purpose of this review due to the difficulty in quantifying more intangible themes associated with model validation (and their subjective interpretations) [Sterman, 2002]. This also enables more perspectives to be considered in the identification of patterns and trends than would otherwise be possible using a purely numerical analysis of citations [Sterman, 2002]. A combination of human and computer-based processing methods are adopted to analyse opinions captured within this exploratory study. Where automated approaches are applied (relating to pattern recognition and statistical analysis - see section 4.3 for further details), manual cross-checking ensures that validation themes are consistent with patterns observed from the literature study and survey results. An overview of the main methodological steps for structuring survey questions is summarised in Fig. 4.8.

In this instance agent-based modelling and system dynamics are selected as the focus for identifying validation themes. These methods are selected here since they are increasingly used in projections of technology substitution patterns, market disruptions, and the development of planning tools for large-scale events difficult to replicate under normal laboratory conditions [Peres et al., 2010,

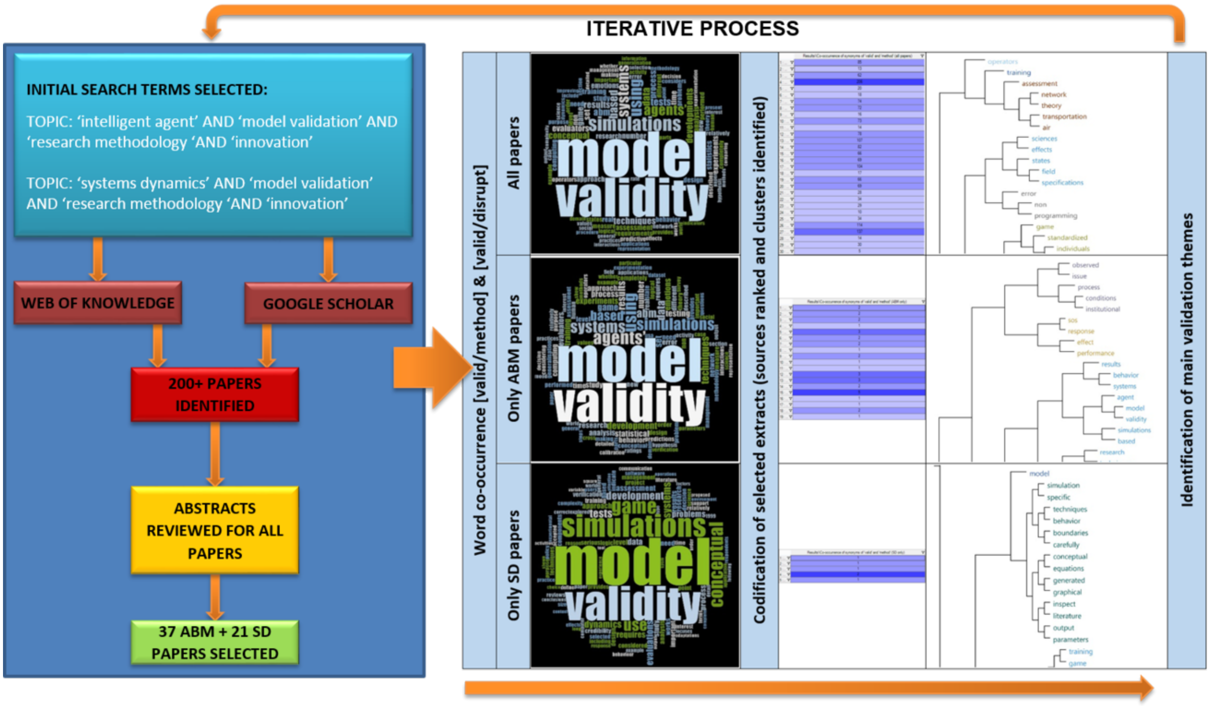


Figure 4.8: Overview of the literature review process used to identify validation themes

Chatterjee and Eliashberg, 1990, Pel et al., 2011, Wang et al., 2014] (see chapter 2). To identify and categorise the procedures available for demonstrating the validity of these forecasting methods, a multiple stage literature review was conducted, as in Fig. 4.8. This process was applied to systematically detect the most frequent terms linked to the validity of each modelling technique, and the credibility of disruptions predicted using these approaches. This inductive approach to identify validation themes combined quantitative referencing of closely-situated key-words within the selected literature (to narrow the search results to the most relevant paragraphs) with a qualitative cross-check of over-lapping phrases, to eliminate unnecessary duplicates.

Additionally, a retrospective appraisal of several historical simulations (such as the annual air traffic forecasts made by the Department for Transport [Government Digital Service, 2013a]) is provided in section 4.6.2 to illustrate some of the challenges observed when reviewing previous attempts at modelling the future. The procedure outlined in Fig. 4.8 (discussed in further detail in section 4.6.3) provided a list of 50 themes relating to computer-generated simulations in forecasting, including themes specific to reliability in modelling disruptive changes. These themes were subsequently used to structure a survey assessing the relative importance of each validation category for different audiences. This survey was intended to obtain empirical data on how academic, commercial, industrial, and public audiences relate to forecasts built on computer modelling, and how the credibility of forecasts may be affected when these models project disruptive changes. Consequently, this survey focused on determining opinions relating to a) modelling and simulation methods used to forecast future events, b) the perceived effectiveness of each validation theme for proving the value of a given forecast, and c) requirements to establish credibility of predicted disruptive changes. Comparing the real-world perspectives obtained from the survey to the categories derived from the literature analysis identifies and enables a ranking of the most effective means of validating forecasting techniques, as well as the prediction features that are most divisive to different audiences, outlined in section 4.6.4.

4.6.2 Retrospective view of simulation challenges

Generating forecasts through modelling and simulation poses numerous challenges. A commonly encountered challenge is the sensitivity of forecast results to the initial modelling assumptions. This is illustrated in Fig. 4.9 to Fig. 4.12 by the degree of variability observed in air traffic forecasts as a consequence of changing initial economic and operating condition assumptions. In the case of Fig. 4.9 and Fig. 4.10, the annual UK Department for Transport (DfT) forecasts perform well versus actual air traffic growth during periods of relative stability, but significant errors appear when major shocks are encountered (with the average error shifting from 1.6% between 2003 and 2007, to greater than 30% between 2007 and 2012 following the economic crisis [Government Digital Service, 2013a]). This shows that financial disruptions had a larger impact on forecasting accuracy than terrorist attacks for air transportation, demonstrating the uncertainty in forecasting sectors closely linked to the economy (for example, the liquidation and dissolution of Long-Term Capital Management L.P. despite the use of sophisticated risk models [MacKenzie, 2003]). Sensitivity studies conducted by the DfT indicate the dependency, and very broad range of possible outcomes, for the forecast number of UK terminal passengers, arising solely from variations in assumed oil prices and national GDP (see Fig. 4.10). The real outcome appears more in line with the low GDP and high oil price scenario shown retrospectively in Fig. 4.10, illustrating the importance of selecting the right initial conditions.

In a separate study, the UK Airports Commission has compared the impact of assuming unconstrained and constrained traffic growth on forecasts of airport capacity, as shown in Fig. 4.11 and Fig. 4.12 [Government Digital Service, 2013b]. In this instance 'unconstrained' and 'constrained' modelling assumptions refer to whether restrictions on airport runway capacity growth are taken into account or not. This demonstrated that under an assumption of no capacity constraints (i.e. continued infrastructure development without obstacles), there was a relatively minor impact on the total traffic predicted across the airports. However, following the introduction of capacity constraints into the model there are notable changes in forecast results (see Fig. 4.12): whilst there is a small percent of growth at heavily constrained airports in this condition (due to some continued development in capability), these airports are now expanding behind overall market growth. Traffic lost at these constrained airports now spills to adjacent airports, leading to greater traffic growth in these regions whilst the aggregated traffic levels remain approximately the same as the unconstrained growth trend (in line with general economic trends) [Government Digital Service, 2013b]. As such, both the DfT and UK Airports Commissions' sensitivity studies illustrate how strong divergence from reality can occur based on initial modelling assumptions.

As well as the challenges associated with the sensitivity of forecasts to the assumptions made in development, there are many challenges encountered when attempting to replicate disruptions and real-world behaviours. This is illustrated by the comparison of recorded air passenger data and the

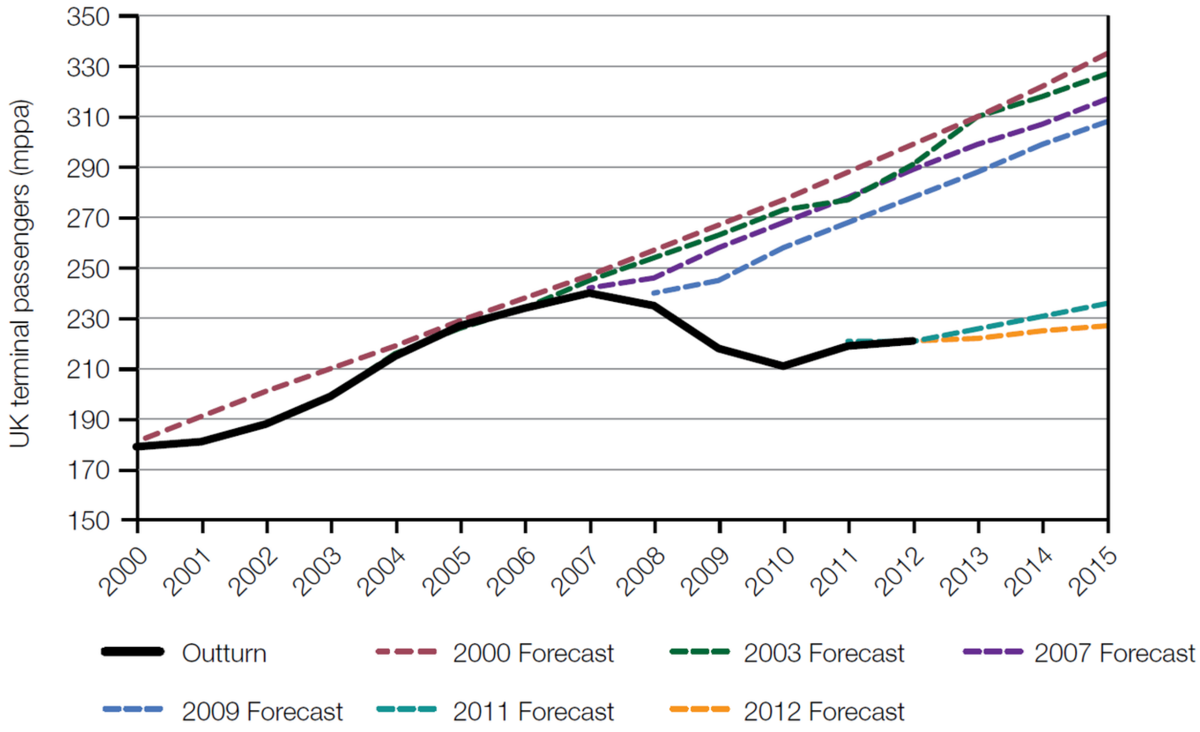


Figure 4.9: Department for Transport air traffic forecast performance [Government Digital Service, 2013a]

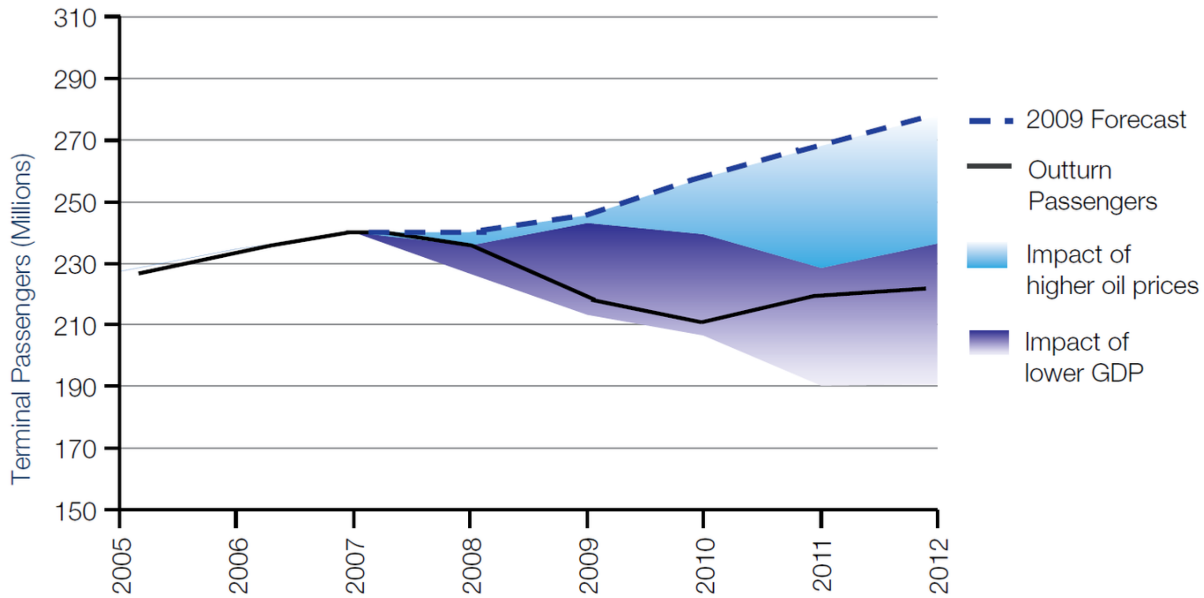


Figure 4.10: Impact of GDP and oil price variation on DfT 2009 forecast [Government Digital Service, 2013a]

forecast passenger numbers in Fig. 4.13 and Fig. 4.14 following the eruption of Eyjafjallajökull in 2010 [Steele and Hollingsworth, 2011]. Whilst the system dynamics model built was able to accurately predict the scale and duration of the disruption to air travellers in the vicinity of the disruption, the simulation results are not intuitively matched to the traffic levels directly preceding or following the

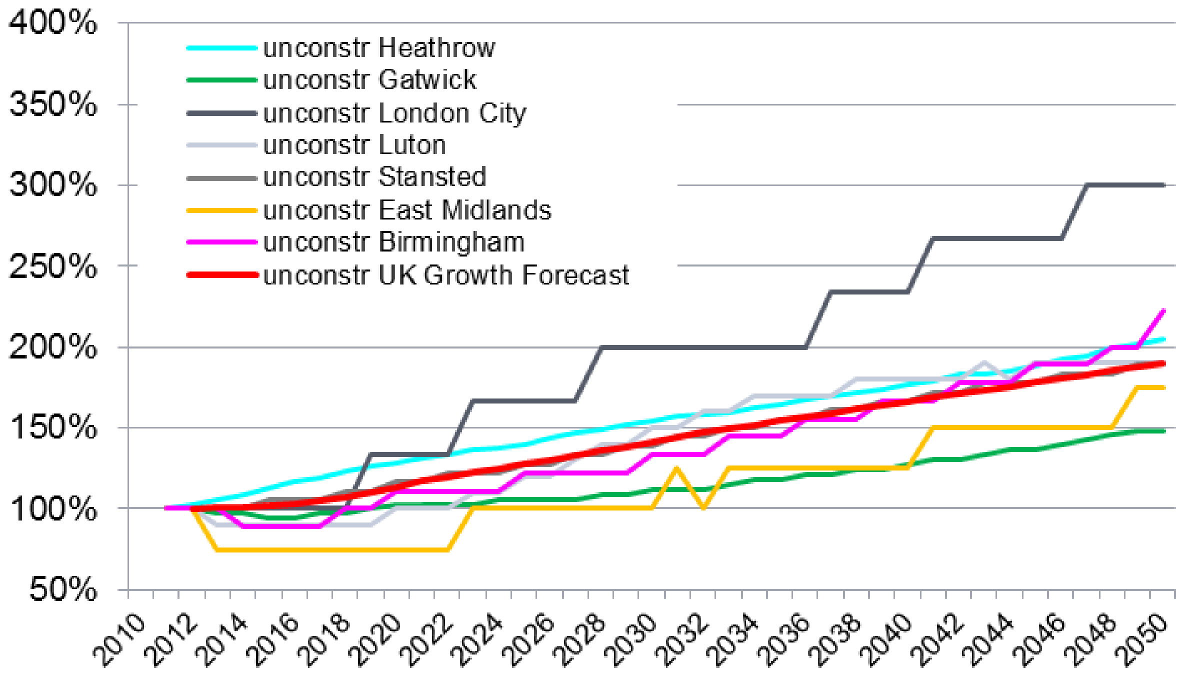


Figure 4.11: Unconstrained Air Traffic Growth (vs. 2011 traffic) [Government Digital Service, 2013b]

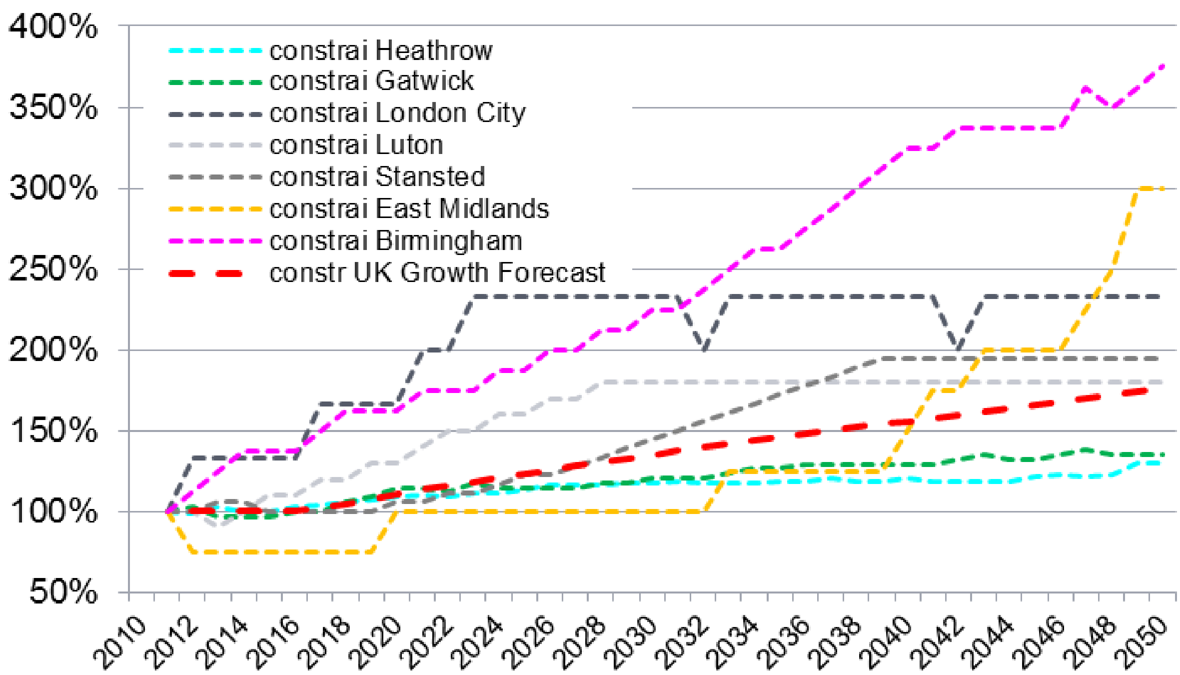


Figure 4.12: Constrained Air Traffic Growth (vs. 2011 traffic) [Government Digital Service, 2013b]

eruption. More specifically, considering the responses shown in Fig. 4.13 and Fig. 4.14, the seasonal variation of passenger numbers is not present in the computer-generated model for the same time period.

Determining the model granularity necessary to capture real-world effects, such as these annual travel patterns, whilst limiting the complexity of models is challenging, which may require that model variables and methods use different levels of granularity at different points to achieve the transparency required for wider acceptance. This requires careful thought regarding the boundaries between influences internal and external to the modelled system, and is also dependent on having sufficient data to extract accurate models of real-world effects. Furthermore, even with detailed consideration of the influences that should and should not be included within a simulation to demonstrate the ability to reproduce disruptive phenomena to an accepted level of robustness and generalisation, it remains difficult to anticipate where the emergent properties of real-world systems will cause actual responses to diverge from predicted results.

The sensitivity of disruptive events to assumed initial conditions provides some indication of the robustness of predictions (as in Fig. 4.15 and Fig. 4.16), albeit in a closed sense. That is to say that sensitivity studies still typically assume model initial conditions and formulation include the necessary variables that ultimately explain disparity between simulated and real-world effects. This therefore illustrates why simulations of disruptions are often regarded as good indicators of trends rather than methods for obtaining exact values [Wang et al., 2014]. For example, in the sensitivity analysis conducted by Steele and Hollingsworth, an impact factor was defined for each transport system being modelled (i.e. air and rail) based on user-defined assessments of the magnitude, start time, and duration of a disruption. The authors have then related these impact factors to the demand for travel, transfer rates between transport modes, and the number of people entering and exiting each transport system at a given time in their systems dynamic model. As such, the sensitivity studies shown in Fig. 4.15 and Fig. 4.16 suggest that high impact events in rail transportation take longer to recover than in aviation [Steele and Hollingsworth, 2011]. This assumes, however, that the relationships defined between impact characteristics and the transport system performance metrics considered in the model capture all of the major real-world effects. Generally, this is unlikely to be the case, as can be seen from trends observed in Fig. 4.15 (examining curves 3, 7, and 9) that suggest that if both the air and rail systems are adversely impacted to a similar degree then some passengers will remain in the air transport system regardless of other options [Steele and Hollingsworth, 2011]. In reality, this does not consider passengers switching to other modes of transport, such as cars and buses, and uncertainty remains over the level of individuals who might decide not to travel under such circumstances, both of which would alleviate the sustained demand seen here [Steele and Hollingsworth, 2011]. Consequently, Steele's study, and many others like it, illustrate how simulations may be able to accurately represent aspects of observed real-life behaviours, but may not always be able to reproduce all external effects and influences.

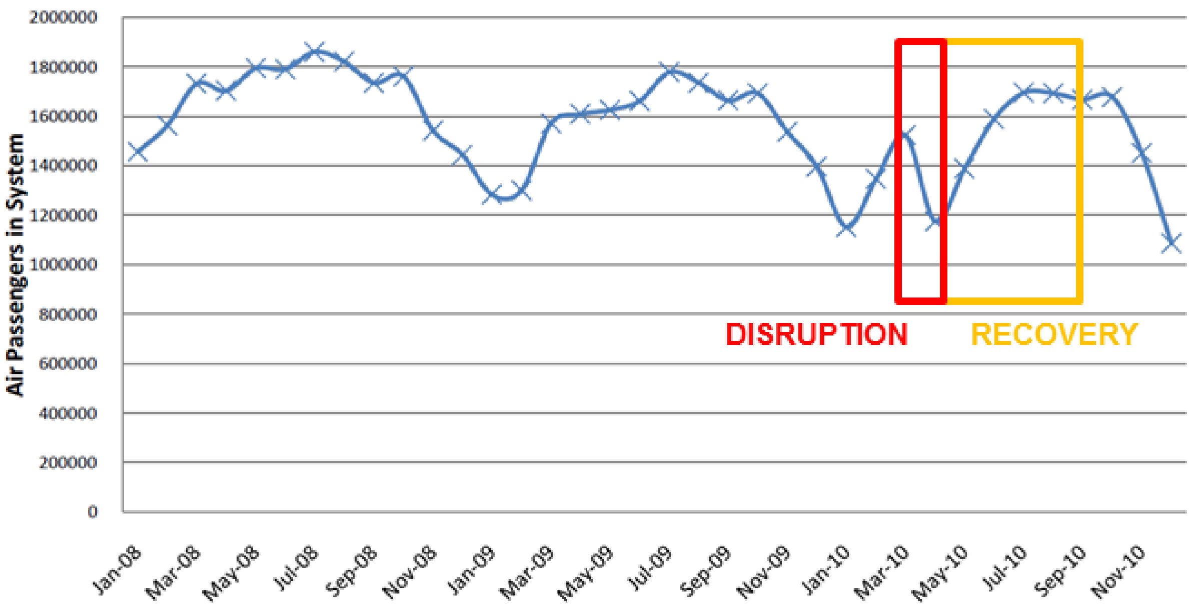


Figure 4.13: Air System data for the defined UK Transport System [Steele and Hollingsworth, 2011]

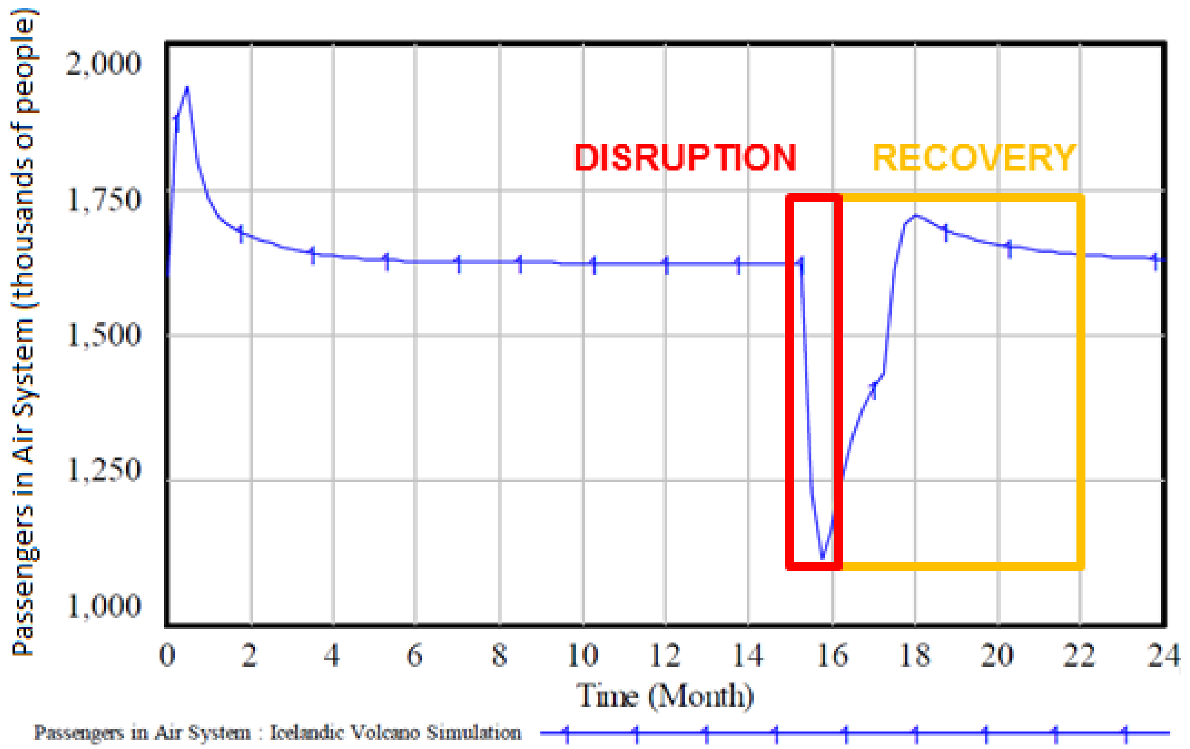


Figure 4.14: Air System data for the simulated UK Transport System [Steele and Hollingsworth, 2011]

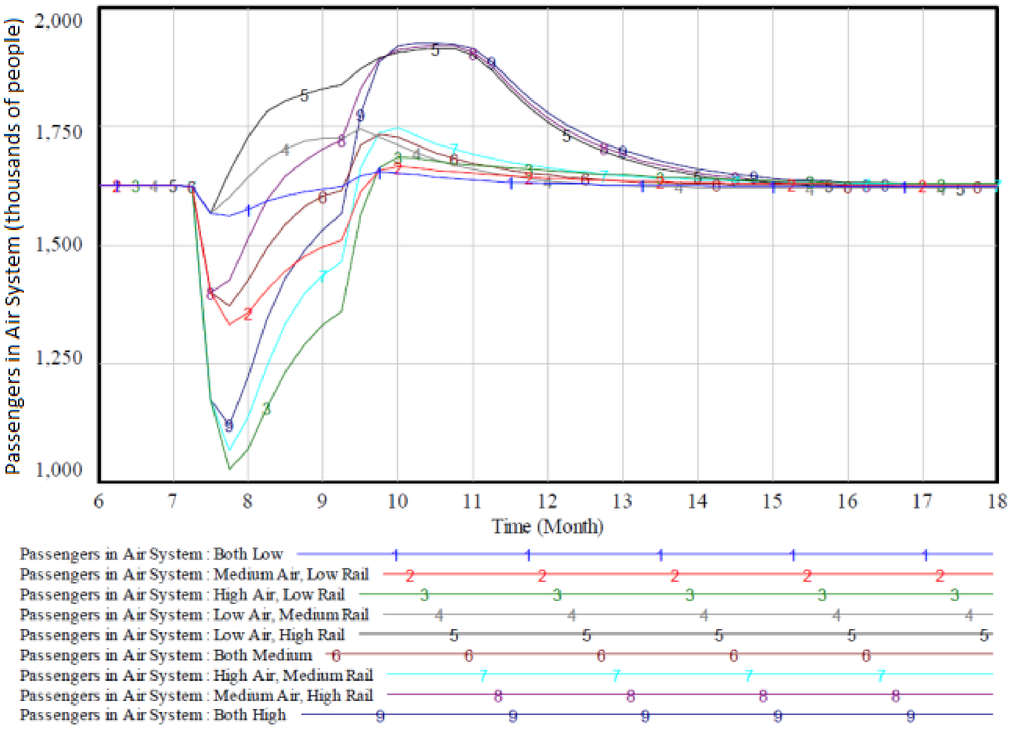


Figure 4.15: Passenger levels in the Air System for different impact ratios [Steele and Hollingsworth, 2011]

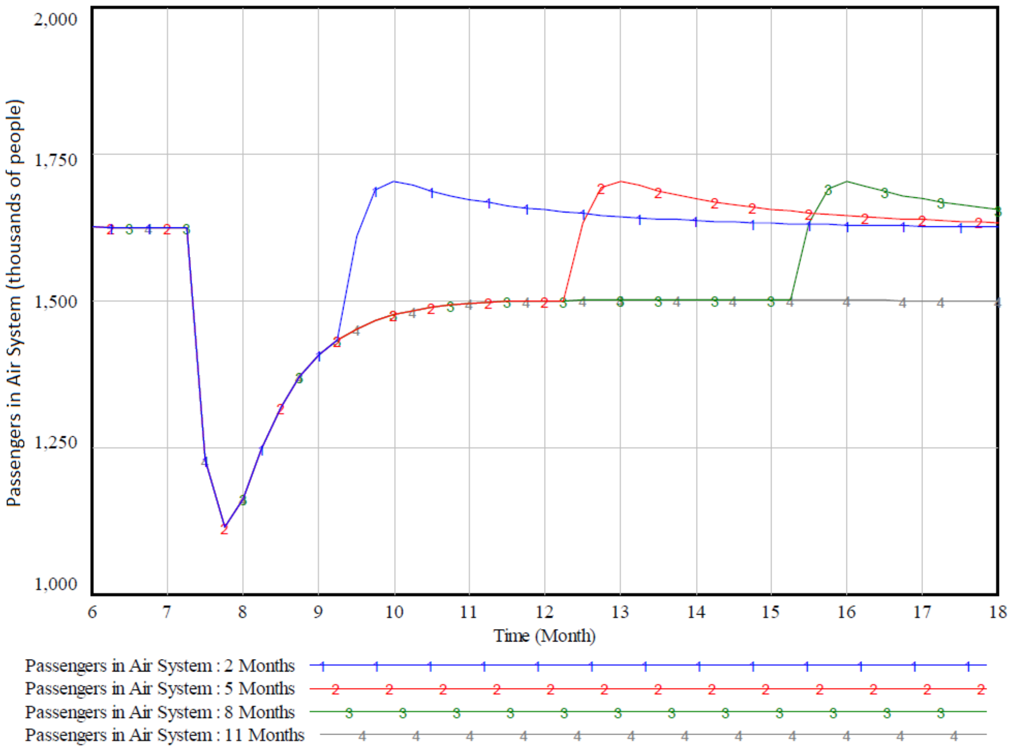


Figure 4.16: Passenger levels in the Air System for different impact durations [Steele and Hollingsworth, 2011]

4.6.3 Identifying validation categories for agent-based and system dynamics modelling

The process of identifying validation categories for computer-generated forecasts began by defining search terms focused on either model or method validity in conjunction with agent-based and system dynamics modelling techniques, as in Fig. 4.8. To identify as many validation traits for these forecasting techniques as possible, the selected keywords were kept deliberately simple (see point 1 below) to avoid unintentionally excluding records spread across different industrial and commercial domains. By scanning the contents of academic journals for these key words (using the Google Scholar and Web of Knowledge academic search engines) over 200 papers were identified that provide insight into the different approaches adopted to demonstrate the credibility of forecast results. By then manually reviewing all of the abstracts for this initial set of academic papers, a further down-selection took place to focus on papers that placed greater emphasis on either reviewing methodological developments or the application of specific simulation techniques for predicting disruptive changes. In this manner, the final set of literature sources to be analysed was identified, as summarised in Table 4.8. The sources recorded here cover a broad range of domains (including agriculture, biology, city planning, ecology, economics, health-care, and transportation, amongst others) in order to identify alternative validation techniques applied within different industries.

Following the initial down-selection, this material was imported into the NVivo qualitative data analysis software package to carry out a systematic assessment of patterns in the literature, enabling the identification of commonly occurring validation themes. This consisted of several stages:

1. **Co-occurrence:** First, a combined text search query was conducted for synonyms of the key terms 'valid' and 'method' occurring in the same paragraph within each literature source. This enabled all of the paragraphs discussing validity to be identified for both ABM and system dynamics modelling techniques from the previously selected sources.
2. **Cross-tabulation:** The results of this combined text search query were then processed using NVivo's auto-code function to generate a 'Node Matrix' based on the paragraphs where co-occurrence had been identified. This produced a hyperlinked reference table of the most commonly occurring terms within the paragraphs of interest across all papers (in this case, terms relating to the validity of methods employed). This step provided a systematic means of ranking the relevance of each literature source to the discussion of model validity, and specific terms within the cross-tabulated results, by assessing the relative frequency and clustering of stemmed terms (based on Pearson's correlation coefficient [Yin et al., 2006]) in these highlighted paragraphs. This is illustrated in the example weighted keyword lists and dendrogram provided in Fig. 4.8 and Fig. 4.17 respectively.
3. **Identification of validation themes from clustered terms:** Using the dendrograms from the cross-tabulation of literature sources (see Fig. 4.17), core themes associated with model validity were identified from the clustered terms relating to ABM and system dynamics techniques. This was based on identifying connecting natural language patterns between key words within each cluster that fitted the context of the overall analysis (i.e. relevant to the validation of simulation methods), as shown in Fig. 4.17.

Table 4.8: Mapping of literature sources to simulation topics

Reference	**Area of applicability**		
	ABM	**SD**	**Disruptions**
[Steele and Hollingsworth, 2011]		X	X
[Carter, 2001]	X	X	
[Celikoglu and Dell'Orco, 2008]	X	X	
[Hahn and DeLaurentis, 2005]	X		X
[Heath et al., 2009]	X		X
[Pinon et al., 2011]		X	X
[Lorenz, 2009]	X	X	
[Bart, 1995]	X		
[Davies et al., 2011]	X		X
[Kuhn et al., 2010]	X		
[Tesfatsion, 2006]	X		
[Tesfatsion, 2002]	X		X
[Epstein, 1999]	X		
[Bonabeau, 2002]	X		
[Borrill and Tesfatsion, 2010]	X		X
[Gulden, 2013]	X		
[Bryson et al., 2007]	X		
[Osman, 2012]	X		
[Berger, 2001]	X		
[Wooldridge, 2009]	X		
[Liu et al., 2011a]		X	
[DeLaurentis et al., 2004]		X	
[ho Lewe et al., 2011]	X		
[Koplin and Skelton, 2012]	X	X	
[Woodward et al., 2008]		X	
[van der Zee et al., 2012]		X	
[Janssen and Ostrom, 2006]	X		
[Scott et al., 2013]		X	
[Henderson-Sellers, 2005]	X		
[Piccioni, 2012]		X	
[Borshchev and Filippov, 2004]	X	X	
[Leblanc, 2014]	X		
[Zhao and DeLaurentis, 2008]	X		X
[Weiss et al., 2013]	X		
[Blanchard, 2010]		X	
[Bousquet and Page, 2004]	X		
[Shoham and Leyton-Brown, 2008]	X		
[Van der Hoog, 2004]	X		
[The Smithsonian Institution, 2012]		X	
[Castle and Crooks, 2006]	X		
[Ahmed et al., 2008]		X	
[Maani, 2009]		X	
[Pfaender and Mavris, 2011]		X	
[Tako and Robinson, 2012]		X	X
[Farmer and Foley, 2009]	X		
[Meadows et al., 1972]		X	
[Nikolai and Madey, 2009]	X		
[Macal and North, 2010]	X		
[DeLaurentis, 2005]	X	X	X
[Both et al., 2012]	X		

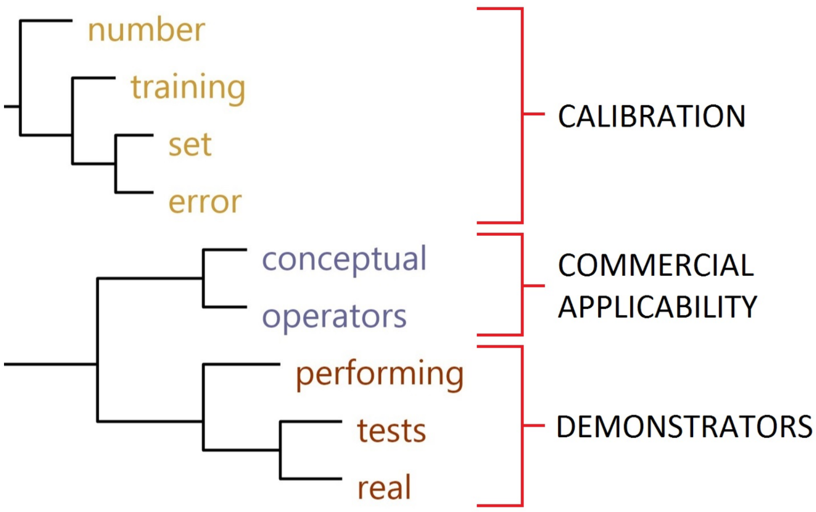


Figure 4.17: Identifying validation themes based on natural language patterns appearing in dendrograms

To identify potential differences in the themes associated with the validation of agent-based and systems dynamics models, the analysis was run again for the two different subsets of papers (ensuring that NVivo's auto-coding function operated on the reduced sets of papers). Similarly, this analysis was repeated to classify challenges specifically associated with modelling disruptions, resulting in the identification and mapping of the 50 unique validation themes given in Table 4.9.

4.6.4 Real-life perspectives on simulation validation and the modelling of disruptions

Having identified and mapped key themes relating to model validation and the simulation of disruptive events from analysis of agent-based and system dynamics literature, a survey was structured (using the Typeform™online survey tool) to assess how academic, industrial, and public audiences perceive the relevance of each theme. To provide some measure of opinions, a Likert scale question was assigned to each of the 50 themes in Table 4.9. Both five and seven point Likert-type scales are commonly used in surveys measuring opinions [Bearden et al., 1993]. This is supported by coding reliability studies which have identified that Likert-type scales become significantly less accurate when the number of scale points drops below five or rises above seven [Cox, 1980, Johns, 2010]. Equally, the use of an odd-number of alternatives has been shown to be important to allow for neutral responses [Cox, 1980]. Whilst correlations and reliability have generally been found to be stronger when using seven point variants of Likert scales, five point scales have typically been found to be less confusing and increase response rates [Cox, 1980, Babakus and Mangold, 1992]. Further, fewer points has been noted as preferable in situations where the target audience is expected to have a more general knowledge of a topic, as opposed to subject matter expertise [Cox, 1980]. As such, a five point Likert-type scale was used in this study to ensure responses were reliable, accurately coded, and accessible to the target audience. A transcript of the resulting survey is provided in Appendix B.

Table 4.9: Validation themes identified in clustering analysis and corresponding mean scores for alternative occupations

ID Code	Validation themes	Definition	Validation themes identified				Survey Question	Mean validation theme score for alt. occupations				
			any method	ABM only	SD only	disruptions		Overall	Academic	C & PS	Industrial	Mixed
ANA	Analogies	Use of comparisons as means of justification			X		18	3.21	3.47	2.71	3.14	3.25
ASC	Assessment criteria	Clear rationale behind chosen measures of the future	X		X		21	2.45	2.47	2.29	2.59	2.17
CAL	Calibration against historical trends	Ability to reproduce previously encountered conditions	X	X	X	X	43	3.06	2.95	2.86	3.24	2.92
CAP	Capturing individuality	Ability to reproduce human idiosyncrasies	X				54	3.21	3.47	3.14	3.24	2.75
CAU	Causality	Ability to trace dependencies between events			X	X	58	3.21	3.32	3.14	3.21	3.08
CLA	Classification/pattern recognition	Ability to match patterns to existing templates			X		46	3.55	3.42	3.29	3.62	3.75
COA	Commercial applicability	Ability to extend forecasts to fit other purposes	X	X	X	X	15	3.19	3.32	3.14	3.17	3.08
COI	Commercial implications	Ease of use in commercial environments				X	28	2.96	2.84	2.57	3.07	3.08
COD	Competing dynamics/forces	Clear identification of shifting model dynamics	X	X	X		24	3.93	3.68	3.71	4.07	4.08
CON	Context	Explanation of study background	X				16	3.76	3.53	3.43	4.14	3.42
COP	Contingency planning	Anticipating and preparing for large-scale disruptions				X	51	3.34	3.37	3.14	3.14	3.92
DAT	Data sources	Identification of study data origins	X				34	4.04	4.00	3.29	4.14	4.33
DEM	Demonstrators	Ability to reproduce results from prototypes	X				40	3.12	3.11	3.29	3.14	3.00
ERR	Error-checking (coding)	Evidence of eliminating errors from software	X				36	3.82	3.84	3.43	3.93	3.75
EXP	Exploration	Ability to detect new patterns and trends				X	47	3.51	3.47	3.43	3.59	3.42
EXT	External systems-wide effects	Ability to deduce implications of "knock-on effects"				X	56	3.24	2.95	2.86	3.48	3.33
FIL	Filtration	Ability of methods to eliminate 'background noise'			X	X	49/50	2.90	2.79	2.79	2.88	3.21
FIT	Fit-for-purpose	Ability to answer the original question of interest	X			X	13	2.81	2.89	2.71	2.76	2.83
GEN	Generalisation	Ability to apply forecasts in other industries		X			17	3.45	2.89	3.29	3.83	3.50
GRO	Group Model Building	Evidence of any group-thinking biases		X			22	3.79	3.74	3.71	3.83	3.83
HEA	Health monitoring	Frequency of comparative performance assessments			X		27	3.81	3.68	3.71	3.86	3.92
HIN	Hindsight vs. foresight	Using the past as a guide to the future				X	38	3.60	3.74	2.86	3.90	3.08
HUM	Human Factors	Ability to predict intangible values (such as 'comfort')		X			53	4.01	3.84	4.14	4.00	4.25
IMP	Impact locality/hierarchical effects	Ability to predict the extent and localisation of disruptions				X	59	3.55	3.63	3.86	3.45	3.50
INF	Informativeness	Ability to provide sufficient information for decision-making		X	X		52	3.33	3.53	3.86	3.14	3.17
INI	Initial conditions	Evidence of exploration of different starting assumptions	X	X			35	3.85	3.63	3.71	3.93	4.08
INT	Intuitiveness/illustrativeness	Clear rationale behind chosen analogies				X	19	2.79	3.05	2.43	2.76	2.67
LOC	Localised research influences	Evidence of industry specific biases		X			20	3.87	3.74	3.57	3.97	4.00
MET	Method triangulation	Evidence of comparisons to alternative forecasting methods	X		X		26	2.39	2.21	2.43	2.55	2.25
MER	Methodological rigour	Clear rationale behind chosen forecasting approach	X	X	X		30	4.40	4.42	4.43	4.38	4.42
MIC	Micro vs. macro approach	Use of aggregated results				X	25	3.18	3.00	3.14	3.21	3.42
MOB	Model boundaries	Evidence of clearly defined limits of model validity		X		X	31	4.16	4.32	3.86	4.28	3.83
MOD	Model development	Evidence of successive refinement of forecasting model	X	X	X		32	3.46	3.42	3.29	3.48	3.58
MUL	Multiple evaluation criteria	Ability to forecast and assess multiple criteria simultaneously				X	57	3.19	2.89	3.57	3.17	3.50
NET	Network/propagation effects	Ability to map the "knock-on effects" of changes	X			X	61	3.75	3.74	3.71	3.76	3.75
NOV	Novelty	Ability to rationalise the unknown or unexpected	X				48	2.91	2.84	3.14	2.86	3.00
PER	Perspectives	Evidence of assessing different interpretations of forecasts	X				33	4.09	3.74	3.86	4.34	4.17
PRI	Prioritisation/ranking capability	Expectation of informativeness over prolonged timescales				X	44	2.78	2.68	2.86	2.90	2.58
PRO	Proven results	Evidence of existing successful forecasting predictions		X	X		39	3.48	3.42	3.29	3.72	3.08
QUA	Quality of data	Use of incomplete, or extrapolated, datasets		X	X		23	3.51	3.47	2.71	3.55	3.92
REA	Reactiveness	Ability to accurately reproduce responses to disruptions		X		X	60	2.93	2.89	2.71	3.17	2.50
REP	Researcher's paradigm/subjectivity	Evidence of researcher specific biases	X	X	X		12	4.24	4.00	4.29	4.38	4.25
RES	Resilience	Using past disruptions as a guide to future large-scale events				X	41	3.93	3.74	3.57	4.17	3.83
ROO	Root cause/problem identification	Ability to correctly identify main challenges		X			45	3.55	3.21	3.43	3.79	3.58
SCA	Scalability/industrialisation	Explanation of planned improvements and refinements		X			37	3.57	3.63	3.43	3.52	3.67
SIM	Simulating realistic behaviours	Ability to reproduce recognisable patterns	X	X	X		55	3.13	3.42	2.71	3.17	2.83
STR	Strategic planning	Evidence of existing large-scale strategic successes				X	14	3.43	3.16	3.29	3.72	3.25
SUS	Sustained accuracy	Versatility of forecast versus dissimilar historical scenarios			X		42	2.75	2.63	3.14	2.69	2.83
TRA	Traceability	Evidence of well-referenced documentation	X		X		29	4.22	4.37	3.86	4.28	4.08

To avoid biasing the results of this survey participants were selected across a diverse spectrum of technical expertise. In this sense, respondents included individuals who were already well-versed with modelling and simulation practices, but also those who had limited or no experience in the field. This was true of all of the sector domains considered, meaning that technical expertise was not solely concentrated in the industrial category, and that an understanding of theoretical principles was not limited to individuals from academia. Respondents were asked to participate via email in most cases, but where possible individuals were also contacted in person or by phone to help provide context for the request.

Table 4.10: Highest ranking validation themes vs. occupation

Rank	Validation themes (ID Code) vs. occupation [a]				
	Overall	Academic	C & PS	Industrial	Mixed
1	MER	MER	MER	MER	MER
2	REP	TRA	REP	REP	DAT
3	TRA	MOB	HUM	PER	HUM
4	MOB	DAT	IMP	MOB	REP
5	PER	REP	INF	TRA	PER
6	DAT	ERR	MOB	RES	COD
7	HUM	HUM	PER	CON	INI
8	RES	GRO	TRA	DAT	TRA
9	COD	HIN	COD	COD	LOC
10	LOC	LOC	GRO	HUM	COP

[a.] Green = common to all occupational subsets
Blue = common to 4 out of 5 occupational subsets
Purple = common to 3 out of 5 occupational subsets
Orange = common to 2 out of 5 occupational subsets
Red = unique within highest rankings for occupational subsets

A total of 67 participants submitted full responses to the survey. This consisted of 19 individuals working purely in an academic environment, 7 in either a commercial or public sector environment, 29 in a purely industrial environment, and 12 in a mixed capacity (i.e. occupations spanning a combination of the above categories, or that includes charities, self-employed, and unemployed participants). The mean Likert scale value obtained when considering the full group of participants is shown against each validation theme in the 'Overall' column in Table 4.9. This provides a baseline ranking of the themes identified from the literature analysis. By subsequently comparing these baseline scores to the mean Likert scale values for each theme based on specific occupational subsets (as shown in the 'Academic', ‘Commercial & Public Sector’, ‘Industrial’, and ‘Mixed’ columns[3]), it is possible to examine the effect of varying occupational cultures on an individual’s validation priorities. The results of this analysis are summarised in the comparison of the highest ranking validation themes identified for each occupational subset presented in Table 4.10.

This comparative analysis of highest rankings suggests that some validation themes are seen as prerequisites for credible forecasting across all occupational groups. These include demonstrations of methodological rigour, providing evidence of traceability, elaborating the researcher’s subjectivity, and exploring the human factors that may or may not have an influence on the simulation. At the other end of the spectrum, this analysis suggests academic communities place increased importance on error-checking and using hindsight as a basis for foresight, whilst commercial and public sector workers are more focused on impact locality and informativeness. This fits with the intended rigour of academic processes as well as the day-to-day decision based nature of commercial and public sectors environments. Similarly, the focus on ‘context’ within industrial workplaces agrees with the highly product-based mentality of this occupational subset (i.e. targeting activities for ‘end’ application). Although the survey results agree well with the simple retrospective view of simulation challenges (see section 4.6.2) in that the sensitivity of simulations to initial model conditions, competing environmental dynamics, and development assumptions are a high priority for audiences, this additional level of detail helps to more clearly define modelling expectations and requirements.

4.6.5 Consequences for the technology classification and substitutions models

From this exploratory review, there are several implications that can be taken forward in subsequent modelling and simulation activities. Firstly, beyond reproducing historical conditions, there is a clear need to explore the sensitivity of any models to assumed initial conditions. This provides a means to examine the degree of variability and uncertainty associated with any starting assumptions, and correctly identify the influence of these assumptions in determining model behaviour. To account for the impact of this variability on any conclusions, statistical ranking, benchmarking, and permutation testing methods are applied to the technology classification model developed in chapter 5, whilst sensitivity studies are presented for a range of both assumed and derived simulation parameters in the technology substitution model developed in chapter 6. There is also a need to clearly define the influences that will be internal and external to the model (i.e. the model scope), to provide the intended audience with appropriate expectations of model limitations. An initial outline of model scope appears from the problem structuring exercises presented in chapter 3. In the context of the technology classification model, this means recognising that the statistical approach taken is suitable for correlation analysis, but does not by itself provide a detailed causal understanding of events. The causal influence of socio-economic effects is instead examined through a historical review of the extracted technology data in chapter 5, although this refers to the input datasets rather than the model. Meanwhile, for the technology substitution model the scope is established through the definition of essential model verification criteria in chapter 6, along with a detailed description of the model structure and

[3]Here ‘C & PS’ stands for ‘Commercial and Public Sector’ and ‘Mixed’ represents those individuals who work in multiple domains, such as employees who work in both academic and industrial contexts

incorporated features. Following the historical review of technology development datasets in chapter 5, an examination of the adoption data and model components corresponding to each technology is provided in chapter 6, to ensure that the datasets used in the model are representative of observed real-life effects.

The provisions listed above for the models developed in subsequent chapters contribute towards methodological rigour, one of the key validation themes identified as a prerequisite for all of the audiences considered. However, additional measures are required to satisfy the other prevalent validation themes identified. The reflection on philosophical and methodological stances, presented in chapter 3, is therefore required to provide background on the researcher's paradigm. This also provides an indication of other human factors that could adversely influence the work beyond those typically accounted for by human-error (which are addressed separately through error-checking procedures employed in subsequent chapters). Traceability meanwhile is particularly important when reproducing work based on modelling and simulation. In this study this is addressed through the disclosure of assumptions, datasets, methods, and tools used in the analysis where possible, amongst reviews of evidence considered in structuring modelling decisions. For this reason, a comprehensive series of appendices is provided to enable the reader to reconstruct the models described. Ultimately though, this is only considering those themes identified as most critical to demonstrating validity in modelling and simulation, but as Table 4.9 suggests, many other facets exist.

4.7 Detailed method selection

Based on the technology classification problem considered, bibliometric data available, and methods discussed in sections 4.3.1 to 4.3.6, the techniques described in the following sections have been selected for use in this study.

4.7.1 Technology Life Cycle stage matching process

For those technologies where evidence for determining the transitions between different stages of the TLC has either not been found or is incomplete, a *nearest neighbour* pattern recognition approach has been explored, following the work of Gao [Gao et al., 2013], to locate the points where shifts between cycle stages occur. A supervised learning approach is taken since it is not believed necessary to re-establish the validity of the assigned categories as the TLC model is well-established and widely recognised as a sensible basis for classifying technological maturity. Equally, the *nearest neighbour* approach is a common industry standard, so no further development of this is proposed within the current study. It is important to recall here though that technologies may in fact shift continually and non-sequentially between the different stages of the Technology Life Cycle, as mentioned earlier in sections 2.1 and 2.4. This is reflected in the outputs from the nearest neighbour pattern recognition approach illustrated in section 5.6. In doing so, this analysis provides a measure of *progress* along the Technology Life Cycle S-curve, but does not compare the mode (i.e. *shape*) of the observed substitution to the typical classification patterns described by Adner (see section 2.5). However, for the technologies considered in chapters 5 and 6, literature evidence identifies the transitions between stages, and so the *nearest neighbour* methodology in chapter 5 is only given as a provision for expansion to other technologies in future studies.

4.7.2 Identification of significant patent indicator groups

To identify bibliometric indicator groups that could form the basis of a data-driven technology classification model, a combination of DTW and the 'PAM' variant of K-Medoids clustering is applied in this study. For the initial feature alignment and distance measurement stages of this process, DTW is still widely recognised as the classification benchmark to beat (see section 4.3.2), and so this study does not attempt to advance feature alignment processes beyond this. Unlike the TLC stage matching process which is based on a well-established technology maturity model, this study is assuming that a classification system based on the modes of substitution outlined in section 2.5 is not intrinsically valid. For this reason, an unsupervised learning approach is adopted here to eliminate human biases in determining whether a classification system based on reactive and presumptive technological substitutions is valid, before defining a classification rule system. This means that predicted clusters can be labelled, even if labels are only available for a small number of observed samples representative of the desired classes, or if none of the samples are absolutely defined. This is particularly useful if the technique is to be expanded to a wider population of technologies, as obtaining evidence of the applicable mode of substitution that gave rise to the current technology can be time-consuming, and in some cases the evidence may not be publicly available (e.g. if dealing with commercially sensitive performance data). Clustering may therefore be able to provide an indication of the likely substitution mode of a technology, without prior training on classes of technologies. Under such circumstances this approach could be applied without the need for collecting performance data, providing that predicted groupings are broadly identifiable from inspection with the suspected modes of substitution. This is of course easier if some examples are known, but means it is no longer a hard requirement.

The 'PAM' variant of K-Medoids is selected here over hierarchical clustering since the expected number of clusters is known from literature (for the technologies considered), and keeping this number fixed enables easier testing of how frequently predicted clusters align with expected groupings. Additionally, a small sample of technologies is evaluated in this study, and as a result computational expense is unlikely to be significant in using the 'PAM' variant of K-Medoids over hierarchical clustering approaches. The Euclidean distance metric is selected for the K-Medoids clustering to ensure consistency with the DTW measures available (see [MathWorks, 2016a]). Amplitude normalisation of the time series further ensures that Euclidean distance measures are not inadvertently biased by observations of high or low values (see section 4.3.4). It is also worth noting that by evaluating the predictive performance of each subset of patent indicator groupings independently it is possible to spot and rank commonly recurring patterns of subsets. This is not possible when using approaches such as Linear Discriminant Analysis, which can assess the impact of individual predictors but not rank the most suitable combinations of indicators.

4.7.3 Ranking of significant patent indicator groups

As the number of technologies considered in this study is relatively small, exhaustive cross-validation approaches provide a feasible means to rank the out-of-sample predictive capabilities of bibliometric indicator subsets that produce significant correlations to expected in-sample technology groupings. Therefore 'leave-p-out' cross-validation approaches are applied, whilst also reducing the risk of over-fitting in the following model building phases [Arlot and Celisse, 2010].

4.7.4 Technology classification model building

The misalignment in time between life cycle stages relative to other technologies can make it difficult to identify common features in time series. This is primarily because the phase variation observed risks artificially inflating data variance, skewing the driving principal components and often disguising underlying data structures [Marron et al., 2015]. Consequently, due to the need to account for phase variance when comparing historical trends for different technologies, and the coupling that exists between adjacent points in growth and adoption curves, functional linear regression is selected to build the time dependent technology classification model developed in this study (see section 4.3.6). The preceding clustering and ranking stages therefore test the suitability of Adner's classification scheme based on complete patent indicator profiles (testing variation and correlation in the patent indicator dimension), whilst functional regression builds time-dependent models for each patent indicator considered in the selected classification scheme.

4.7.5 Sensitivity of technology adoption to chosen modelling parameters

Whilst statistical approaches are well-suited to detecting underlying correlations in historical and experimental datasets, this alone does not provide a detailed understanding of the causation behind associated events. Equally, statistical methods are generally ill-suited to predicting disruptive events and complex interactions. Other simulation techniques, such as system dynamics and ABM, perform better in these areas (see chapter 2 and sections 4.4 and 4.6). Accordingly, to identify causation effects and test the sensitivity of technological substitution patterns to variability arising from real-world socio-technical features not captured in simple bibliometric indicators (such as the influence of competition and more precise economic effects), the fitted regression model is evaluated in a real-time system dynamics environment. Considering the emphasis placed on traceability by survey respondents in section 4.6.4, this is thought to be a sensible first development prior to attempting to capture complex emergence effects using ABM, whilst also providing a baseline for comparisons in subsequent studies.

4.8 Method limitations

Although precautions have been taken to ensure that the methods selected for this study address the challenges in building generalised technology classification and substitution models from bibliometric data as rigorously as possible, there are known limitations that must be recognised. Many of these stem from the fact that technologies have been selected for which evidence is obtainable to indicate the mode of adoption followed. As such, the technologies considered are not from a truly representative cross-section of all industries, and so may provide a better representation of the selected industries rather than a more generalisable result. This evidence-based approach also means that it is time-consuming to locate the necessary material to support classifying technologies as arising from one mode of substitution or another, and to then compile the cleaned patent datasets for analysis. Consequently, a relatively limited number of technologies have been considered in this study, which should be expanded on to increase confidence in findings produced from this work. This also raises the risk that clustering techniques may struggle to produce consistent results for the small number of technologies considered. Furthermore, any statistical or quantitative methods used for classification in chapter 5 are unlikely to provide real depth of knowledge beyond the detection of correlations behind patent trends when used in isolation. Ultimately some degree of causal exploration, whether through case study descriptions, system dynamics modelling, or expert elicitation is required to shed more light on the underlying influences shaping technology substitution behaviours. These are incorporated as best as possible by the technology timelines in chapter 5, and adoption trends and substitution modelling activities in chapter 6, but without further study these can only be considered as exploratory at this stage.

Other data-specific issues that could arise relate to the use of patent searches and the need to resample data based on variable length time series. In relation to the former, patent search results and records can vary to a large extent depending on the database and exact search terms used, although overall trends once normalised should remain consistent with other studies of this nature. In relation to the latter, functional linear regression requires all technology case studies to be based on the same number of time samples. Consequently, as discussed in section 4.3.6, linear interpolation is used to ensure consistency between the number of observations, whilst possibly introducing some small errors which are not considered to be significant.

4.9 Conclusions from review of modelling and validation techniques

Building on the research questions and strategy outlined in chapter 3, this chapter has examined in more detail the implications of investigating technology substitutions using modelling and simulation techniques. This began with a summary of the selection criteria used to identify relevant technologies for evaluation in this analysis, accompanied by a brief discussion of the general means available for gauging the progress of technological development. This was then followed by an outline of the bibliometric and market data sources selected to provide an insight into historically observed substitution patterns. An overview of potential techniques to address specific challenges regarding the comparison of time series and capturing real-world behaviours in simulated environments was presented in sections 4.3 and 4.4 respectively. The means of assessing whether these challenges are met was considered in section 4.5, where a summary of goodness-of-fit and statistical measures highlighted a range of evaluation criteria that should be considered in demonstrating the practicality of computer-generated models.

Inherently there are additional challenges with any form of computer-generated techniques which are not as evident in other forms of hypothesis testing, many of which arise from the added complexity associated with the creation and interpretation of these models. This is often due to a lack of immediate transparency or intuitiveness that occurs when hiding much of the derivation and execution behind a screen of automation. Consequently, cross-checking of results against historical data is encouraged as best practice. This includes sensitivity studies to test initial parameters and assumptions, and compare the behaviours demonstrated in the models to real-world complexities.

An inductive assessment of modelling and simulation literature was subsequently applied, combined with empirical data from a systematically structured survey, to identify, map, and rank themes relating to the validity of computational forecasting techniques (to determine the most critical influences on professed model credibility for technological forecasting). 50 validation themes have been presented in Table 4.9 (derived using a systematic literature review process), along with their applicability to agent-based and system dynamics modelling techniques, and general simulations of disruptive changes. These themes have been scored against responses from a mixed audience of academic, commercial, and industrial participants (amongst others). The results reveal the perceived effectiveness, by different occupational groups, of each theme for establishing the credibility of a simulation. Themes that affect all participants, such as demonstrating methodological rigour, providing evidence of traceability, scrutinising the researcher's subjectivity, and exploring human factors that may have an influence on the simulation, are unsurprisingly perceived as prerequisites of a credible forecast. The survey data also shows specific occupational trends, such as the relative importance to commercial participants of the degree of prediction informativeness and elaborating the impact locality (as they are frequently required to act on the information received), and the emphasis on error-checking in academic communities. Appropriate techniques were then selected and outlined for the stages envisaged in answering the research questions posed in chapter 3, with a preliminary discussion of potential method limitations. With this knowledge in hand and the relevant statistical methods now selected, the next chapter provides a detailed account of the construction of the technology classification model.

Chapter 5

Building a technology classification model from Technology Life Cycle features

Based on the review of challenges associated with the use of modelling and simulations in forecasting, the means of determining goodness-of-fit, and the resulting method selection outlined in the last chapter, this chapter explains how these elements have contributed to the derivation of a technology substitution classification model. The methodological stages considered in this analysis are summarised in the framework shown in Fig. 5.1 to provide a more coherent picture of the methods adopted in the following sections.

This analysis proceeds by first defining the patent search and extraction strategies applied, before reviewing the datasets compiled against historical observations. Next, technology datasets are segmented in accordance with Technology Life Cycle stages, enabling statistical comparison, identification, and ranking of the most suitable data predictors. The most promising patent indicator dimensions are then selected and adapted to construct the final classification model. Ultimately, the predictive performance of the classification model is evaluated against the expected substitution labels for the technologies considered and measures of out-of-sample prediction capabilities. This analysis consequently provides the basis for the technology substitution model developed in chapter 6.

5.1 Patent indicator definitions

The work of Gao et al. identifies a range of studies that have been conducted previously based on using either single or multiple bibliometric indicators to investigate technological development and performance [Gao et al., 2013]. Their review of these methods concluded that multiple patent indicators are required to avoid generating potentially unreliable findings as a result of using a single indicator extracted from patent data. As such, the *nearest neighbour* classification process developed in Gao's study to assess progress through the Technology Life Cycle S-curve proposes 13 separate patent indicators. The current study has accordingly reproduced these metrics where possible, resulting in 10 patent indicators (i.e. producing time series for each technology with 10 dimensions). The remaining

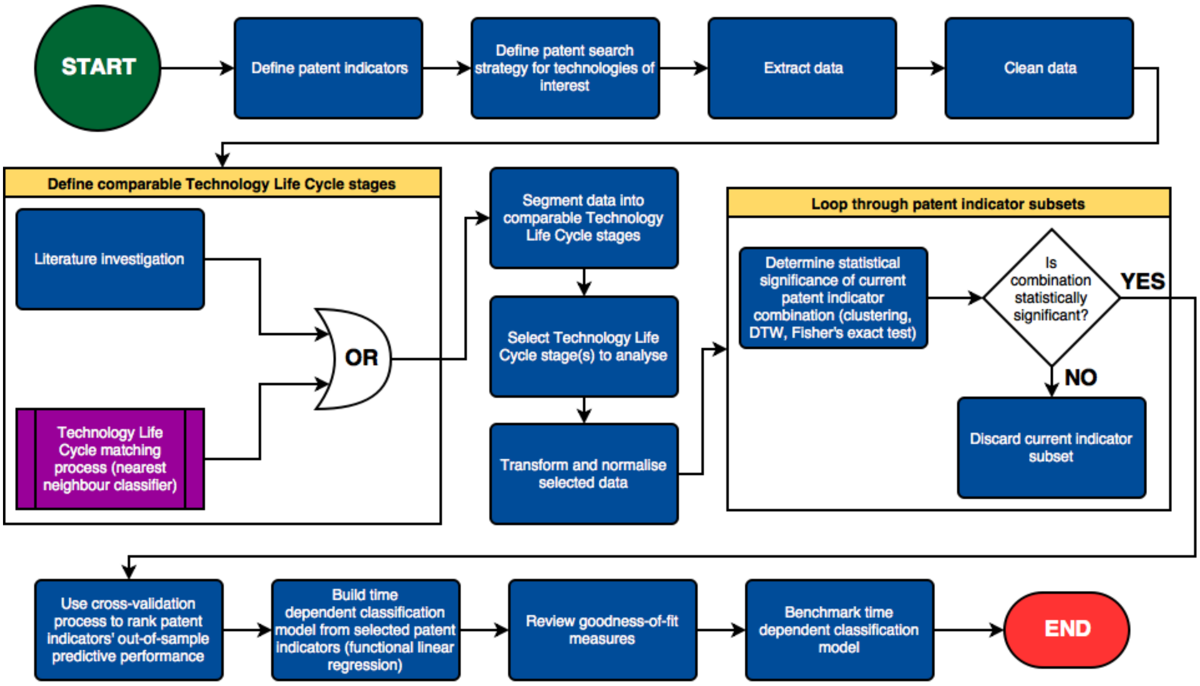


Figure 5.1: Overview of the analysis framework developed in this chapter

three metrics from the previous list of indicators were specific to the Derwent Innovation Index [www.emeraldinsight.com, 2003], which was not used in this study due to the limited ability to bulk export the results from this database. Table 5.1 summarises the bibliometric indicators extracted for each technology within this analysis. The dependencies between each of these indicators during different TLC stages is explored in the cross-correlation analysis presented in section 2.4 and Table 4 of [Gao et al., 2013]. Aside from indicator 1, all of the other patent counts considered in Table 5.1 are based on the earliest priority date of the collated patent family records.

Apart from using the Questel-Orbit FamPat database instead of the Derwent Innovation Index (DII), the indicator definitions and assumptions in this study are consistent with those outlined in sections 2.1.1 to 2.1.5 of [Gao et al., 2013]. The only other notable difference is that the Questel-Orbit patent records are not automatically designated as corporate, non-corporate, or individual patent assignees. Consequently, counts of corporate and non-corporate indicators (which would otherwise be based on this assignee designation) are determined instead from the *Family Normalized Assignee Name* field in the patent records, which corresponds to corporate designations.

5.2 Search strategy and terms for identifying relevant patent profiles

Previous bibliometric studies have explored the different ways that patent records can be correctly identified for a given field or topic [Verbeek et al., 2002, Schmoch, 1997, Albino et al., 2014, Rizzi et al., 2014, Mao et al., 2015, Dong et al., 2012, WIPO, 2009, Helm et al., 2014]. Whilst filtering search results based on technology classification categories is generally preferred to ensure a more rigorous search strategy [Albino et al., 2014], it is advisable to keep the steps that supplement or

Table 5.1: Bibliometric indicators used in this study (based on the work of Gao et al. [Gao et al., 2013])

Indicator No.	Name	Description
1	Application	Number of patents in Questel-Orbit by application year
2	Priority	Number of patents in Questel-Orbit by priority year
3	Corporate	Number of corporates in Questel-Orbit by priority year
4	Non-corporate	Number of non-corporates in Questel-Orbit by priority year
5	Inventor	Number of groups of inventors in Questel-Orbit by priority year
6	Literature	Number of backward citations to literature in Questel-Orbit by priority year
7	Patent citation	Number of backward citations to patents in Questel-Orbit by priority year
8	IPC	Number of IPCs (4-digit) in Questel-Orbit by priority year
9	IPC top 5	Number of patents of top 5 IPCs in Questel-Orbit by priority year
10	IPC top 10	Number of patents of top 10 IPCs in Questel-Orbit by priority year

remove patents from search queries to a minimum, to maintain data consistency and repeatability [Helm et al., 2014]. Accordingly, the search queries in this analysis are based primarily on filtering by International Patent Classification (IPC v2017.01) or Cooperative Patent Classification (CPC) labels, based on WIPO search strategy guidelines [Trippe, 2015]. Where possible, IPC categories have been reused from previous studies to replicate existing search queries so as to extract comparative datasets, or based on expert defined groupings such as the European Patent Office's Y02 classification which relates to climate change mitigation technologies. Otherwise, keyword search terms and IPC labels are combined that focus on matching closely adjoining instances of each search term (or their common synonyms). Using IPC technology category filters in this manner ensures that a higher level of relevance and repeatability is achieved. To that end, the final search queries are presented in Table 5.2 along with the number of records retrieved.

5.3 Patent indicator data extraction process

Using the technology classification categories, and where applicable the keywords in Table 5.2, the results of these search queries were exported in batches of up to 10,000 records in a tabulated HTML format. Only a representative patent record from each relevant FamPat group was exported, to avoid duplication of records across multiple jurisdictions. Each record included key patent information and full details of both cited patent and non-patent literature references within the current record. As some searches generated very large numbers of records (i.e. hundreds of thousands), batch processing enabled large quantities of records to be handled in manageable formats, but required batches to be subsequently imported into a tool capable of processing the volumes of data considered. For this purpose, MATLAB was used, and a script (provided in Appendix C) was developed to convert each HTML batch file into a corresponding .MAT file (based on an existing conversion script), ready for data cleaning processes.

Table 5.2: Technologies considered in study, classification, and patent data search terms

Case study	Class	Orbit patent search keywords	IPC or CPC categories	No. of patent families
Compact Fluorescent Lamp	R	(compact+ or CFL+ or (energ+ s (sav+ or low+))) AND fluores+	CPC: Y02B-020/16+ OR Y02B-020/18+ OR Y02B-020/19+	1,169 (21/07/2017)
Electric vehicles	P	--	CPC: Y02T-010/62+ OR Y02T-010/64+ OR Y02T-010/70+ OR Y02T-010/72+ OR Y02T-090/1+	100,870 (24/07/2017)
Fiber optics (data transfer)	R	((fiber+ or fibre+) 3d optic+)	IPC: G02B OR H04B OR C03B OR C03C OR D01C OR D04H OR D06L OR G02F OR G06E OR G06K OR G11B OR G11C OR H02G OR H03K OR H04J OR H04N OR G01P	176,299 (20/07/2017)
Geothermal electricity	P	--	CPC: Y02E-010/1+	5,272 (24/07/2017)
Halogen lights	R	--	CPC: Y02B-020/12+	645 (24/07/2017)
Hydro electricity	P	--	CPC: Y02E-010/2+	46,125 (24/07/2017)
Impact/Dot-matrix printers	R	((impact+ or (dot+ or matri+) or (daisy 1w wheel+)) 3d print+)	IPC: G03G OR B41J OR G06F OR G06K OR H04N OR G06T OR G02B OR H04L OR G01R OR G03C OR B41M OR G03B OR B65H	24,993 (24/07/2017)
Incandescent lights	P	Incandescen+ or filament+	IPC: F21H OR F21L OR F21S OR F21V OR F21W OR F21Y	17,597 (03/08/2017)
Ink jet printer	R	(ink+ 3d jet+ 3d print+)	IPC: B41J-002/01 OR G03G OR B41J OR G06F OR G06K OR H04N OR G06T OR G02B OR H04L OR G01R OR G03C OR B41M OR G03B OR B65H	46,135 (24/07/2017)
Internet	R	(internet+ 3d protocol+ 3d suite+) OR (computer+ 1w network+)	IPC: G06F OR H04L OR G06N OR H04K OR G09F	42,861 (24/07/2017)
Landline telephones	P	(((land_line+ or main_line+ or home or fixed_line+ or wire_line+) 3d (+phone)) OR (speaking telegraph+) OR (telephon+)) NOT (mobil+ or (cell+ 3d (+phon+ or communi+)) or smart_phon+ or port+)	IPC: H04B OR H01Q OR H01P OR H04J OR G01R OR H04Q OR H01H OR H04M OR H04R OR G10L	139,895 (03/08/2017)
Laser printer	R	(laser+ 3d print+)	IPC: G03G OR B41J OR G06F OR G06K OR H04N OR G06T OR G02B OR H04L OR G01R OR G03C OR B41M OR G03B OR B65H	17,827 (24/07/2017)
LED lights	R	--	CPC: Y02B-020/3+	8,596 (24/07/2017)
Linear Fluorescent Tube lights	R	((fluores+ 3d (lamp+ or light+ or tube+))) NOT (compact or (energ+ 3d sav+))	IPC: F21K OR F21L OR F21S OR F21V OR F21W OR F21Y	25,126 (24/07/2017)
Nuclear energy	P	--	CPC: Y02E-030+	60,017 (24/07/2017)
Solar PV	P	--	CPC: Y02E-010/5+ OR Y02E-010/6+	112,068 (24/07/2017)
Solar thermal electricity	P	--	CPC: Y02E-010/4+ OR Y02E-010/6+	91,553 (24/07/2017)
TFT-LCD	R	((((thin film+) 1w transistor+) or TFT+) AND (((liquid crystal+) 1w display+) or LCD)) or TFT_LCD	IPC: G02F-001/13	5,181 (24/07/2017)
Thermal printers	R	(thermal+ 2d print+)	IPC: G03G OR B41J OR G06F OR G06K OR H04N OR G06T OR G02B OR H04L OR G01R OR G03C OR B41M OR G03B OR B65H	23,388 (24/07/2017)
Tide-wave-ocean electricity	P	--	CPC: Y02E-010/28+ OR Y02E-010/3+	19,224 (24/07/2017)
Turbojet	P	((Gas w turbin+) or (jet+ w engine+) or turbo_fan+ or turbo_prop+ or turbo_jet+ or turbo_shaft+ or prop_fan+ or ((open w rotor+) 3d (engine+ or technolog+ or counter_rotat+)))	IPC: B60K OR B60L OR B60P OR B60V OR B61B OR B61C OR B62D OR B63B OR B63H OR B64C OR B64D OR B64F OR B64G OR F01D OR F02B OR F02C OR F02K	71,024 (24/07/2017)
Wind electricity	P	--	CPC: Y02E-010/7+	67,035 (24/07/2017)
Wireless data transfer	R	(Wireless 3d data 3d trans+)	IPC: H03K OR H04H OR H04W OR G06K OR G06T	17,188 (24/07/2017)

5.4 Patent indicator data cleaning process

Whilst the consistency of the Questel-Orbit patent data is of a high standard, several steps are required to extract patent indicator metrics from this data. This is based on WIPO preprocessing guidelines [Trippe, 2015], to ensure that the datasets are translated into a tabulated format suitable for the following automated analysis processes, and to correct any easily rectifiable data-entry errors in the extracted data (such as the omission of application or priority dates from the relevant columns when these dates are available elsewhere). This allows an accurate chronology of patent events to be established. The procedure initially involves removing any non-breaking space values in tabulated cells (which would interfere with later citation counts), leading and trailing white spaces from column headings, and then translating column headings into a format recognisable by MATLAB (i.e. replacing any spaces, slashes, brackets, full stops or hyphens with underscores). Column headings are then used to define variables in a MATLAB table, whilst a generic 'counter' variable is appended to the table to enable the construction of pivot tables.

Having transformed the data into a recognised table format, the script (provided in Appendix C) then identifies records that include valid date entries. Unique corporation, non-corporation, and inventor IDs are then appended to the tabulated records, based on determining the similarity that exists between entries observed in these fields. Next, the script cycles through each record individually, extracting the application and priority dates where present, for each patent family (this involves scanning all priority dates where multiple priority dates are listed against a single record and identifying the earliest date). At this point, the script also counts the number of references and patents cited against each record, and maps all references to included IPC categories to the correct IPC count tally (based on [World Intellectual Property Organization, 2015]). This enables the number of distinct IPC subclasses for a patent family to be counted, and is used later when recombined with the corresponding tallies from every other patent family record to rank the top 5 and 10 most heavily associated IPC subclasses with a developing technology for each year.

For those records where valid dates were not located (typically less than 5% of records), the script checks if any other dates exist against each record from the 'Basic Year', 'Application Year', or 'Priority Year' fields. 'Priority Year' should always be the earliest of these dates, representing the original conception of the idea, rather than the date at which the application was filed with the patent office. Equally, all dates are checked to ensure that none are earlier than 1790 (when the earliest known US patent was recorded, representing the world's earliest patent registration system), as any dates recorded before this are likely to be errors. Once missing dates have been imputed where possible, the script determines the time period defined by the current batch of records, and updates the global time frame for the current technology as required. The bibliometric indicator counts in Table 5.1 are then compiled for each year considered in the current batch of records, and the batch is marked as complete. These steps are then repeated for the next batch. In this way, a collection of summary indicator count tables are built representing each batch of records. These tables are then combined into an overall summary table for each technology, taking care to expand each batch of results for years with 'zero' records, so that corresponding years match when summing table rows. To verify that the MATLAB data extraction and cleaning processes functioned as planned, the output counts of the MATLAB scripts for several sample batches were compared with an equivalent process using Excel pivot tables. This comparison showed that in some instances of formatting issues, the MATLAB scripts were more successful than Excel in filtering out blank values, but that in both cases the overall count values generated corresponded closely to those expected.

5.5 Timeline of events relative to extracted patent profiles

In parallel to the extraction of bibliometric data for the case studies considered, a chronology of historical events has been compiled for each technology based on timelines provided in previous studies. Events have been manually reviewed and grouped based on their timing and perceived relevance. These timelines and event labels are depicted graphically with the corresponding patent profile in Fig. 5.2 to 5.24 and discussed in the following sections. Full details of these timelines, event groupings, and respective sources are provided in Appendix A. It should be noted that the patent profiles generally tail-off after 2011 for most of the technologies considered, as it takes some years for patent records to be fully registered globally and subsequently accounted for in the Questel-Orbit FamPat database. This also varies depending on the field of development and associated volume of patents. Consequently, there are some features and significant events discussed below that are not depicted in the later years of the displayed development trends, although some can be observed separately in the technology adoption profiles discussed in the next chapter. For the purposes of the following statistical and model building analysis, the patent datasets have all been trimmed to use only data points prior to 2012, to avoid this tail-off of data points introducing phantom data artefacts into the analysis. Equally, the statistical analysis uses inverse hyperbolic sine transforms of the timelines presented here to avoid unfairly skewing results based on trends in the second half of the twentieth century (when a significant increase in global patenting activities took place that could otherwise influence any patterns identified). More generally, the patent trends observed are also susceptible to varying levels of 'noise' in the data. This is evident for technologies where fewer patent records have been sourced, whilst those with plentiful patent record entries generally show noticeably smoother trends. To prevent any noise from inadvertently dominating patterns identified in the statistical analysis that follows, technologies with insufficient records were subsequently removed prior to compiling the final list presented in Table 5.2 and examined here, as noted by the selection criteria in section 4.1.

5.5.1 Compact Fluorescent Lamps (CFLs)

The first patent record in this dataset (GB0535897) based on the search terms in Table 5.2 is from 1938, and entitled 'Improvements relating to fluorescent materials for use in electric discharge devices'. This occurs shortly after the first fluorescent tube lights are installed in 1933, and a year after Linear Fluorescent Lights are first commercialised in 1937 (label 1 in Fig. 5.2). However, the development of Compact Fluorescent Lamps takes place substantially later when in 1972 John Campbell patents the first practical CFL (label 2), prompting Philips to develop an electronic ballast CFL in 1979, before first commercialisation in 1980 (label 3). Development activities next accelerated around 1990 (label 4), possibly corresponding with Earth Day in April of that year, which has been credited with having a significant impact on the United States' awareness of energy efficiency, climate change, and ozone depletion [Sandahl et al., 2006]. This also occurred close to Philips' invention in 1991 of a magnetic induction CFL that achieved a lifetime of 60,000 hours. Beyond this, the next noticeable pick up in development occurs around 2000 (label 5) when the U.S. west coast suffers an energy crisis that leads to rolling blackouts, inspiring massive regional CFL promotions and giveaways in 2001. From 2010, the phase out of incandescent light bulbs in different parts of the world (label 6) also led to an increase in CFL adoption, although this is only partially visible in Fig. 5.2 as the patent records from 2011 onwards are not yet all accounted for.

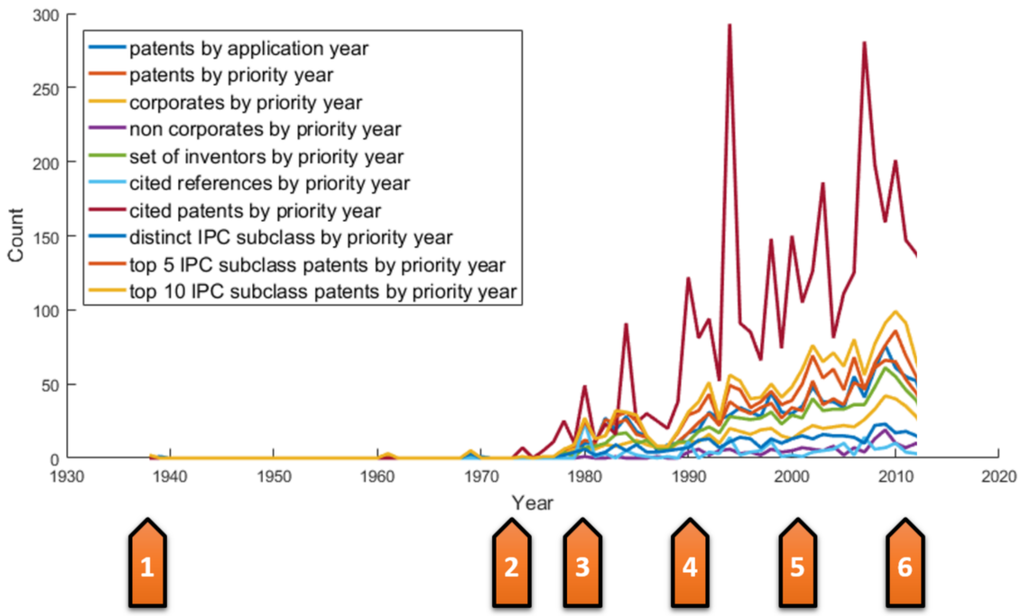


Figure 5.2: Development trends for CFLs relative to historical events

5.5.2 Electric vehicles

The first patent record in this dataset (US540) based on the search terms in Table 5.2 is from 1837 and relates to the design of a locomotive that used a hydraulic pressure accumulator. Accumulators of this type have since been used in regenerative braking systems in hybrid and battery electric vehicles (an example can be seen in U.S. patent US8297198). However, in terms of pure electrical systems, the earliest electric motor and vehicle designs also emerge around this time (label 1 in Fig. 5.3). In particular, the Hungarian inventor Ányos Jedlik is alleged to have constructed an early type of electric motor in 1828 (shortly followed by the U.S. maths professor Joseph Henry in 1831), the Scottish inventor Robert Anderson creates the first crude electric carriage powered by non-rechargeable primary cells between 1832 and 1839, and Thomas and Emily Davenport develop the first rotary direct current electric motor for a miniature electric railcar in 1834. In 1837 and 1841 the first large-scale electric cars were built by the Scottish chemist Robert Davidson in Aberdeen. These were based on galvanic cells and could travel just over a mile with a 6 ton payload, but were destroyed by railway workers who considered them a threat to their livelihood (despite poor commercial viability at the time). The next major milestone (label

2) occurs in the early 1880s when several inventors independently built electric tricycles and buggies. This included vehicles developed in 1881 by Gaston Planté (France), Charles Jeantaud and Camille Alphonse Faure (France), William Ayrton and John Perry (UK), and in 1884 Andrew Riker's tricycle (USA) and the first practical production electric vehicle by Thomas Parker (UK).

The first commercial success of electric vehicles occurred after the development of the 'Electrobat' in 1894 by Henry G. Morris and Pedro G. Salom. 'Electrobat II' was demonstrated over the next two years, and in 1897 Samuel's Electric Carriage and Wagon Company was established in New York and Walter Bersey's cabs in London (label 3). These vehicles had ranges of approximately 20 to 30 miles using the lead-acid battery technology of the time. By 1900, electric vehicles were in their prime as the top-selling vehicle type: in the U.S, approximately 28% of cars produced and 38% of vehicles on the road were powered by electricity.

This state does not last long though, as by 1902 problems had already begun to emerge. Fallout arising from overselling equity stakes in the Electric Vehicle Company damaged the concept of electric vehicles in the minds of investors and customers, whilst negative press circulated from the death of two spectators when the Baker Motor Vehicle 'Torpedo' crashed during a speed trial (label 4). This situation was compounded by the bank panic and recession of 1907 (partly caused by the 'Lead Cab Trust' attempting to build a monopoly), and the first practical electric automobile starter invented by Charles Kettering in 1912, which ironically makes it easier to start the previously unwieldy hand crank starter on petrol vehicles (label 5). Finally, in 1913 mass production of the Ford Model T dealt a fatal blow to early-era electric cars. Following World War I, only a handful of electric vehicle manufacturers survived as developments in petrol vehicles greatly accelerated. By the 1920s, electric vehicles are practically non-existent.

Although battery developments continued slowly (reinvigorated by the launch of Sputnik in 1957 - label 6 in Fig. 5.3), this situation remained largely unchanged until the OPEC oil embargo of 1973 (label 7) which renewed interest in electric vehicles. This leads to the development of the first modern hybrid car by GE Research Labs in 1982, funding of General Motors EV1 in 1988 (which achieved ranges over 160 miles using NiMh batteries in 1999), and California's Zero Emission Vehicle (ZEV) Mandate in 1990 (label 8). Car manufacturers did not generally accept the ZEV law, and proceeded to gradually weaken it through lawsuits. However, the unveiling of the Toyota Prius and leasing of the EV1 in 1997 (label 9) demonstrated a new commercial viability for battery electric vehicles. Tesla Motors capitalised on this, unveiling the Lithium-Ion powered Tesla Roadster in November 2006, which is largely credited with changing the image of electric cars and encouraging many larger manufacturers to commit to electric car development (label 10). By 2010, mass production of the Nissan Leaf (with a top range and speed of over 100 miles and 90 mph respectively) began in Japan, and goes on to become the first electric car to achieve over 100,000 sales in 2014. In 2017, the 3rd Generation Tesla Model 3 (with over 200+ miles range and a base price of approximately $30,000) began production (label 11). Pure electric cars are now cheaper to own and operate than petrol and diesel vehicles in the UK, US, and Japan, whilst sales have also surged due to the drastic fall in diesel vehicles following the Volkswagen emissions scandal of 2015 [Palmer et al., 2018].

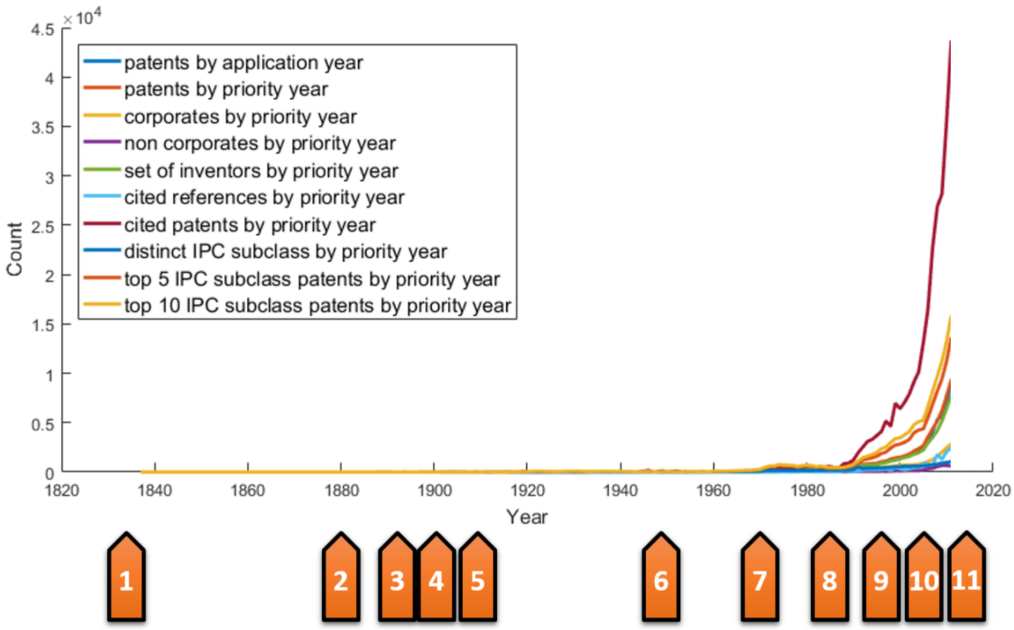


Figure 5.3: Development trends for electric vehicles relative to historical events

5.5.3 Fibre optics

The first patent record in this dataset (JP2992371) based on the search terms in Table 5.2 is from 1946 and relates to the manufacture of optical fibre bundles. This was a year after Ray D. Kell and George Sziklai applied for a patent on transmitting signals through quartz or glass rods (label 1 in Fig. 5.4). Subsequently, in 1954 scientific papers were published in Nature (label 2) based on the work of Harold Horace Hopkins and Narinder S. Kapany, alongside Abraham C. S. van Heel, on using bundles of optical fibres for image transmission. The first simple applications were observed in 1957 with the demonstration of a fibre-optic endoscope, and 1959 with single-mode waveguides (label 3). Simultaneously, theoretical principles for laser operation are defined in 1957/58, leading to the first laser demonstration at Hughes Research Laboratories in 1960. In 1965/66 work by Charles Kao and George Hockham at Standard Telecommunication Laboratories (STL) provided the basis for practical fibre-optics communications after identifying that glass fibres with loss below 20 decibels per kilometre could be made for communications (label 4). This is achieved in 1970 by Robert Maurer, Donald Keck, and Peter Schultz at Corning Glass Works, by manufacturing a single-mode fibre with losses of 16 decibels per kilometre, in the same year that continuous room-temperature semiconductor lasers were first demonstrated.

With practical applications now attainable, John Fulenwider proposes a fibre-optic network for carrying video signals to homes at the International Wire and Cable Symposium in 1972 (label 5), and development accelerates as businesses start to take interest. In 1975, the first experimental and non-experimental fibre optic links were installed in New Jersey and Dorset, followed by a rapidly expanding series of test programs and global government commitments to this communication medium (label 6). This included commitments by AT&T, the British Post Office, and Standard Telephones and Cables to develop a transatlantic fibre cable, TAT-8, in 1978 (completed in 1988). Development continued steadily through the 1980s and 1990s with fibre optic submarine cables providing the backbone for exponentially growing telecommunication and internet services (label 7). This continued until the peak of the Telecom bubble in July 2000 (label 8), which came crashing down in the spring and summer of 2001 (label 9). This significantly impacted fibre optic developments, as shown in Fig. 5.4, which gradually recovered over the ensuing decade.

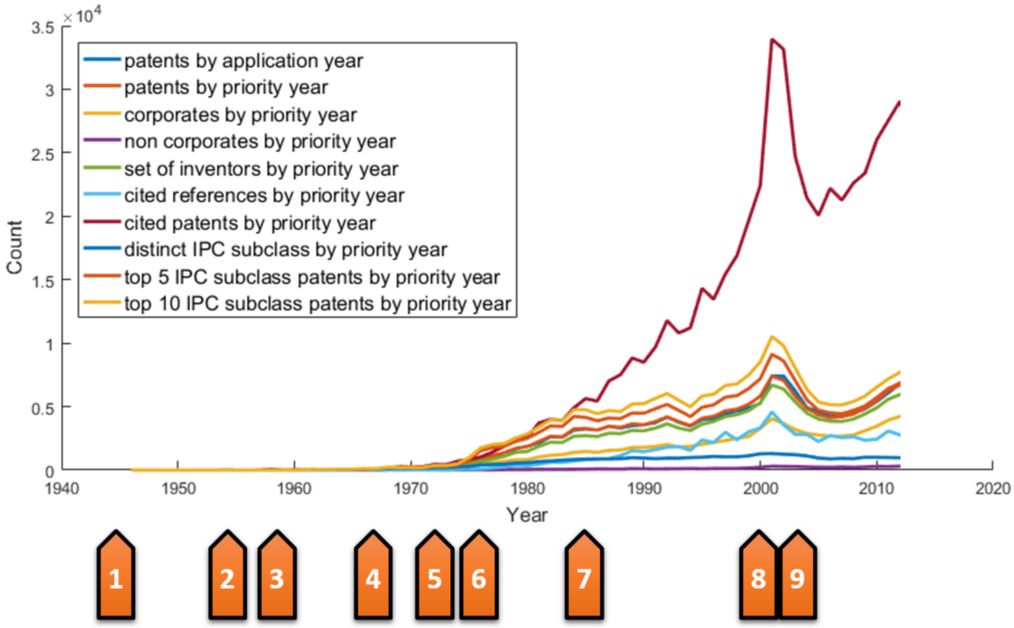


Figure 5.4: Development trends for fibre optics relative to historical events

5.5.4 Geothermal electricity generation

The first patent record in this dataset (US671608) based on the search terms in Table 5.2 is from 1899 and relates to a liquefied-air motor. This corresponds with the earliest developments in geothermal power generation in the early 1890s, when hot springs started to be used to provide residential heat and power. This began on a large-scale in 1892, when the world's first district heating system was constructed in Boise, Idaho, (label 1 in Fig. 5.5) which used water piped from hot springs to heat town buildings, serving over 200 homes and 40 businesses. This was followed in 1900 by using hot springs to heat homes in Klamath Falls, Oregon (label 2), and construction of the world's first dry steam geothermal power plant in Larderello, Italy, by Prince Piero Ginori Conti in 1904 (label 3). However, beyond this, development of geothermal technology remained slow through the subsequent decades until renewed interest arose from the invention of the ground-source heat pump by Professor Carl Nielsen of Ohio State University in 1948 (label 5). There was again a lull in interest, until 1958 when New Zealand built the first geothermal electricity power plant since Larderello, followed shortly by the inauguration of the United States' first large-scale geothermal power plant at The Geysers in 1960 (label 6). Geothermal power generation then began to take root in earnest, and is boosted notably by the 1973 OPEC oil embargo (label 8). This led to the first commercial-scale binary plant commencing operation in California's Imperial Valley in 1980 (label 9). Between 1986 and 2000, interest diminished again as average fossil energy prices steadily declined, with the U.S. Department of Energy (DOE) investment reaching a low of \$15 million in 1990 (label 10). However, during this time, development continued, and in 1989 the world's first hybrid geopressure-geothermal power plant began operating in Pleasant Bayou, Texas. Renewed DOE stimulus efforts also began in 1994 to promote the use of geothermal energy to reduce greenhouse gas emissions (label 11). As oil prices started to rise again after 2000, the U.S. government signed the Energy Policy Act of 2005 into law, providing tax incentives and loan guarantees for various types of energy production, including provisions making geothermal energy more competitive relative to fossil fuels (label 12). This was followed by the American Recovery and Reinvestment Act (ARRA) of 2009, which awarded \$368.2 million to 149 geothermal projects across the United States, providing a further boost to development (label 13).

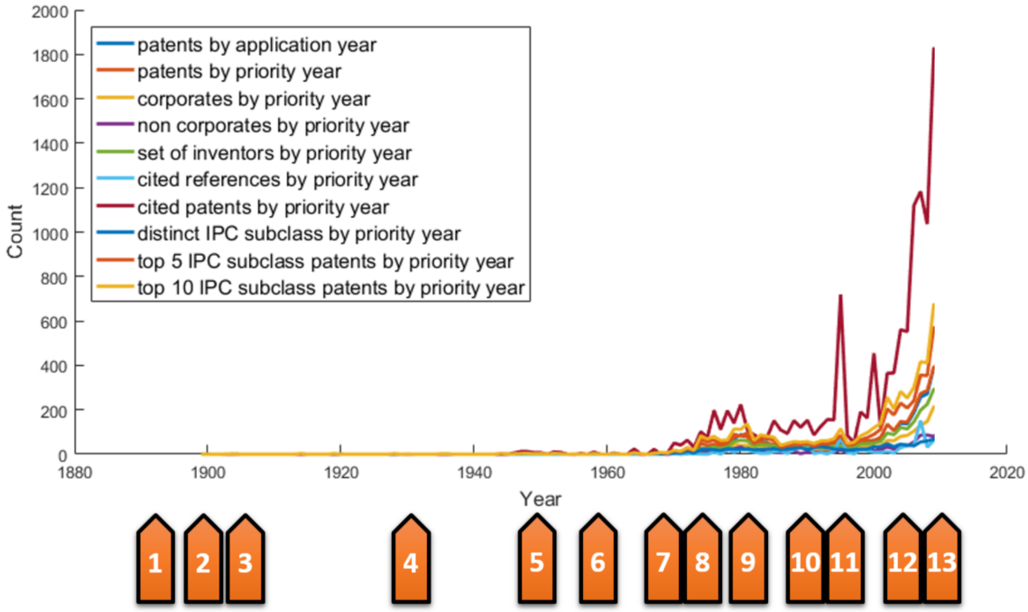


Figure 5.5: Development trends for geothermal electricity relative to historical events

5.5.5 Halogen lights

Halogen lights are a development of tungsten filament lights, the first of which was invented in 1910 by William Coolidge (label 1 in Fig. 5.6). The first patent record in this dataset (FR18339E) based on the search terms in Table 5.2 is from 1912 and relates to an improved tungsten filament light. This is therefore consistent with the associated timescales. The development and commercialisation of fluorescent lights in the late 1930s (label 2) led to increased interest in working with halogens, resulting in Elmer Fridrich and Emmett Wiley inventing the first double-ended tungsten halogen lights at General Electric in 1959 (label 3). Development efforts then accelerated after these initial prototypes, resulting in a commercialised product in 1980 (label 4). Steady development efforts continued as these light bulbs became more widespread, with halogens gaining a substantial proportion of the market initially after the U.S. West coast energy crisis (label 5), and subsequently as incandescent bulbs were phased out globally from 2010 (label 6).

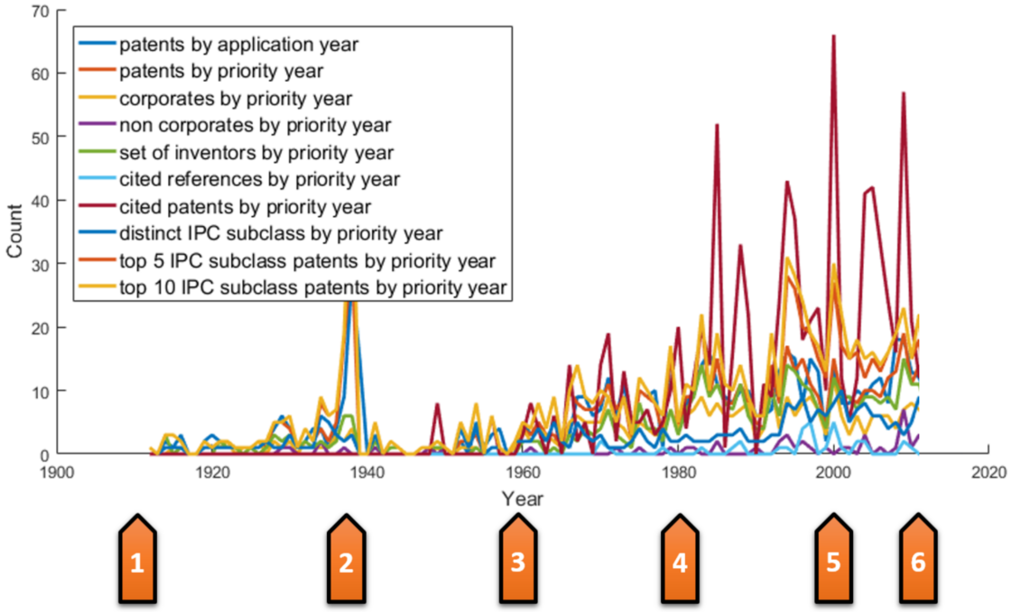


Figure 5.6: Development trends for halogen lights relative to historical events

5.5.6 Hydroelectricity generation

The first patent record in this dataset (US94) based on the search terms in Table 5.2 is from 1836 and relates to a reaction rotary steam engine. This follows the development of the first reaction water turbine by Benoit Fourneyron in 1832 (label 1 in Fig. 5.7), and precedes the invention of the inward-flow water turbine by James B. Francis in 1847 (label 2). However, first power generation began in 1880 with Michigan's Grand Rapids Electric Light and Power Company providing direct current electricity to the Wolverine Chair Factory, followed closely by the provision of hydropowered DC electric street lighting in the city of Niagara Falls, and the world's first DC hydroelectric station in Appleton, Wisconsin, in 1882 (label 3). The introduction of jet-driven turbines (i.e. Pelton machines) in 1889 increased the efficiency of hydropower generation (label 4). This was followed in 1893 by the first dam specifically designed for generating hydropower at Austin, Texas, and the opening of Niagara Falls hydropower station in 1895 (label 5). This initial momentum was tempered in the U.S. by the Federal Water Power Act of 1901 which required permission for hydroelectric plants to be built and operated on any stream large enough for boat traffic (label 6), although growth continued steadily for the next two decades.

The U.S. Federal Power Act of 1920 established the Federal Power Commission, which held the authority to issue licenses for hydropower developments on public lands. This preceded a relative surge in developments (label 7), leading to construction of the Boulder Dam in 1936 (label 8), and the opening of Grand Coulee dam in 1941 (label 9). Between 1940 and 1980, conventional hydropower capacity nearly tripled, encouraged by the oil crisis of 1973 and Public Utility Regulatory Policies Act (PURPA) of 1978 (which mandated that utility companies purchase electricity from qualified independent power producers, including stimulating growth of small-scale hydro plants). However, the U.S. passes the Pacific Northwest Power Planning and Conservation Act in 1980 due to the impact of hydropower facilities on salmon runs in the Columbia river system (label 10). This, and the ensuing protection laws, made obtaining licenses for hydroelectric facilities complex and expensive. The U.S. represented a large proportion of the global hydroelectric market at this time, so when coupled with the decline of average fossil fuel prices between 1986 and 2000, this led to a significant decline in interest in developing hydroelectric technologies, which was only reversed when oil prices started to rise again in 2000 (label 11).

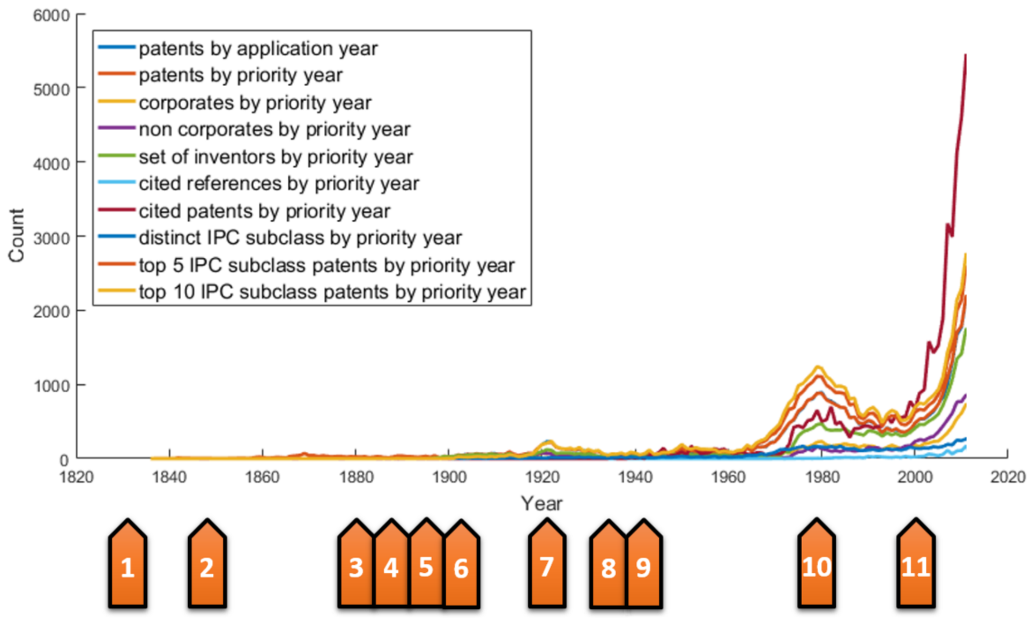


Figure 5.7: Development trends for hydroelectricity relative to historical events

5.5.7 Impact/Dot-matrix printers

The first patent record in this dataset (US1055189) based on the search terms in Table 5.2 is from 1908 and relates to a process for producing three-colour screens. This corresponds to Samuel Simon's use of silk for screen printing in 1907, which quickly becomes popular for printing on fabrics and gives rise to the widest selection of inks of any type of printing (later used in dot-matrix printers). In parallel, mechanical typewriter designs were largely standardised by 1910 when the patent for the first practical electric typewriter (or *teletypewriter*) was filed by Charles and Howard Krum (label 1 in Fig. 5.8). The development of typewriters remained largely stagnant until Rudolf Hell invented and patented an early dot-matrix teletypewriter called the Hellschreiber in 1929, just prior to IBM releasing the Model 01 electric typewriter in 1930 (label 2).

Over two decades later, between 1952 and 1954, Fritz Karl Preikschat filed five patents for his dot-matrix teletypewriter that is built between 1954 and 1956 in Germany (label 4). This was followed closely by the introduction of the first dot-matrix printer by IBM in 1957, and the Xerox 914, the world's first successful plain paper copier, in 1959 (label 5). Interest in dot-matrix printers subsequently increased during the late 1960s. This coincided with the introduction of the Japanese OKI Wiredot serial impact dot-matrix printer in 1968, water-based inks in 1970, and expiration of Xerox's original xerographic copier patents (allowing other manufacturers such as Canon to create xerographic copiers) in the same year (label 6). In 1974 the DECwriter LA36 became one of the first dot-matrix printers to achieve commercial success, whilst stored energy dot-matrix printers also appeared in the market (label 7). This is soon followed in 1978 by the first commercially successful dot-matrix printer for personal computers, Epson's TX-80 (label 8). Development continued growing steadily until 1990/1991 when dot-matrix printer sales peaked (label 9). After this, development declined due to the emergence of cheap ink jet and laser printers. Sales were further impacted by reduced demand for desktop printers from the mid-2000s, driven by the emergence of cloud storage services, tablets, and smartphones, which enabled users to easily access and retrieve thousands of high-resolution images on demand (label 10).

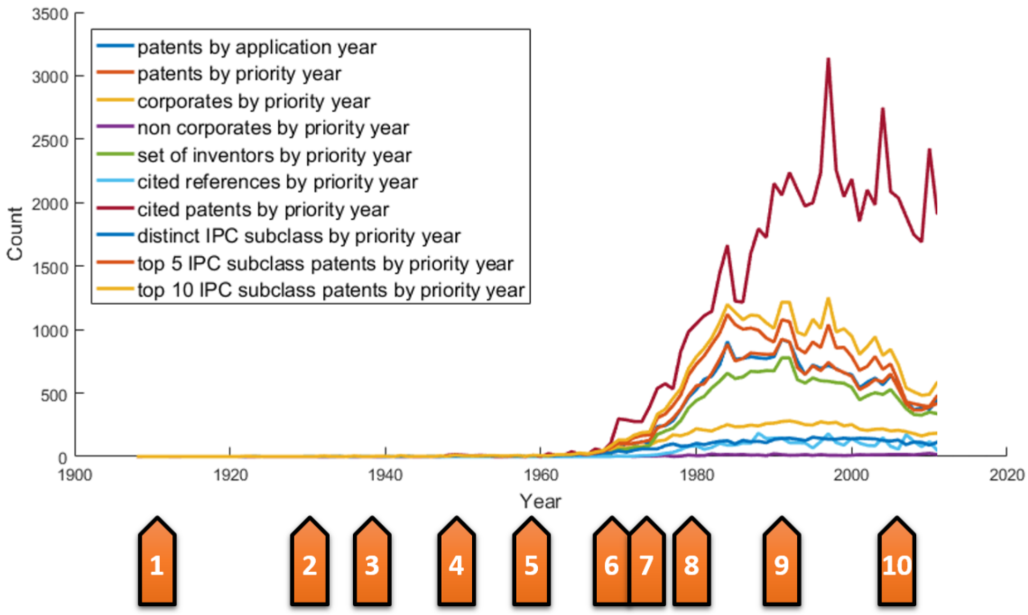


Figure 5.8: Development trends for impact/dot-matrix printers relative to historical events

5.5.8 Incandescent lights

The first patent record in this dataset (GB189601682) based on the search terms in Table 5.2 is dated 1896 and entitled 'Improvements in the Manufacture of Incandescent Bodies for Illuminating Purposes'. Whilst carbon-thread incandescent lights were patented by both Joseph Wilson Swan and Thomas Edison in 1879 (label 1 in Fig. 5.9), developments such as this recorded manufacturing process improvement continued steadily through the 1890s. In parallel, General Electric introduced the first commercial fully enclosed carbon arc light in 1893, prior to Walther Nernst's invention of incandescent lights based on solid state electrolytes in 1897 (label 2). In 1910, Tungsten filament light bulbs were invented (label 3), and some finer performance improvements were engineered in the ensuing decade including the first internally frosted light bulbs in 1925 (label 4). However, incandescent light technology did not advance significantly until the development of halogen lights in 1959 (label 5), and their commercialisation in 1980 (label 6). It is worth noting here that whilst there is considerable overlap between incandescent and halogen lighting technologies (with halogen bulbs being a specific offshoot of incandescent lights - see section 5.5.5), these two lighting types are distinct due to the additional design considerations required for halogen bulbs. These include the need for reinforced glass in halogen bulbs to withstand the higher pressures arising from elevated temperatures in halogen lights. In this regard, sales of pure incandescent lights, and their overall market share, have since dramatically reduced (in many cases replaced by halogen lights initially) due to the global phase-out from 2010 (label 8).

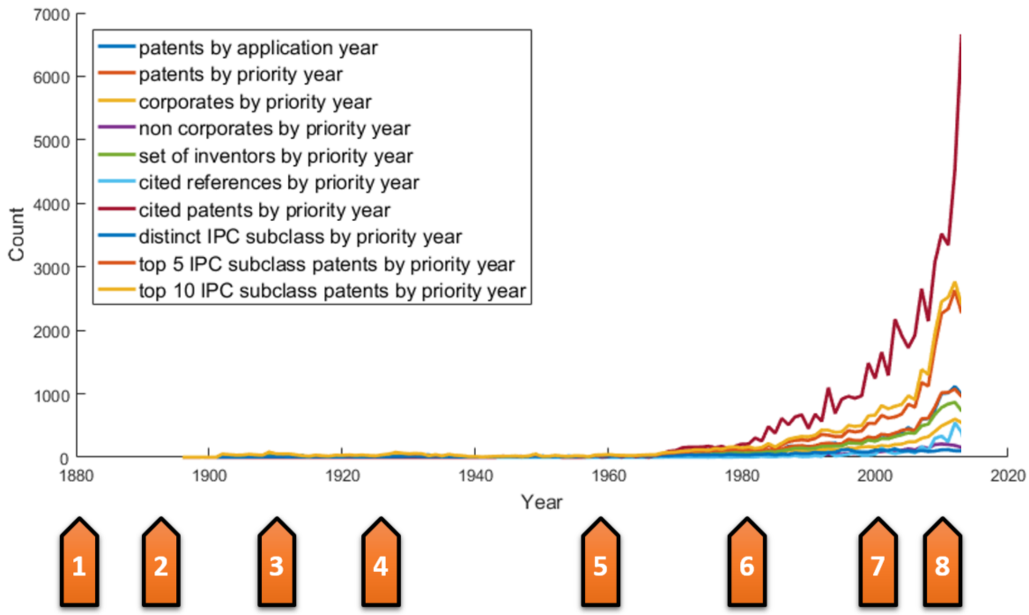


Figure 5.9: Development trends for incandescent lights relative to historical events

5.5.9 Ink jet printers

The first patent record in this dataset (US3060429) based on the search terms in Table 5.2 is from 1958 and relates to a method and apparatus for applying a controlled jet of ink to receiving print media. This patent emerged a year before the introduction of the Xerox 914 plain-paper copier (label 1 in Fig. 5.10), and just prior to Stanford University's development of technology for printing ink droplets using pressure wave patterns in the early 1960s (label 2). As with impact printers, the arrival of water-based inks and expiration of Xerox's patents in 1970 led to increased development (label 3), culminating in the development of thermal drop-on-demand inkjet technology by Canon and Hewlett-Packard in 1977 and 1978 respectively (label 4), with piezoelectric inkjet printers also arriving in 1978. Canon filed the first thermal inkjet patents in Europe and the U.S. in 1979 (label 5). 1984 was another important year for inkjet development, with the introduction of HP's ThinkJet printer (thermal inkjet), the first disposable inkjet cartridges, and the arrival of the Apple Macintosh, which for the first time combined a graphical user interface with a mouse and price that made it viable for many ordinary consumers (label 6). This paved the way for HP's PaintJet in 1987 (the first colour inkjet printer), followed by the DeskJet in 1988 (widely regarded as the industry's 'Model T'), and filing of Xaar's patents for piezoelectric-shear print heads the same year (label 7). Development then continued rapidly until photo-quality inkjet printers appeared around 1996 (label 9), although as with impact printers, interest subsided from the mid-2000s due to the emergence of cloud storage and mobile technologies (label 10).

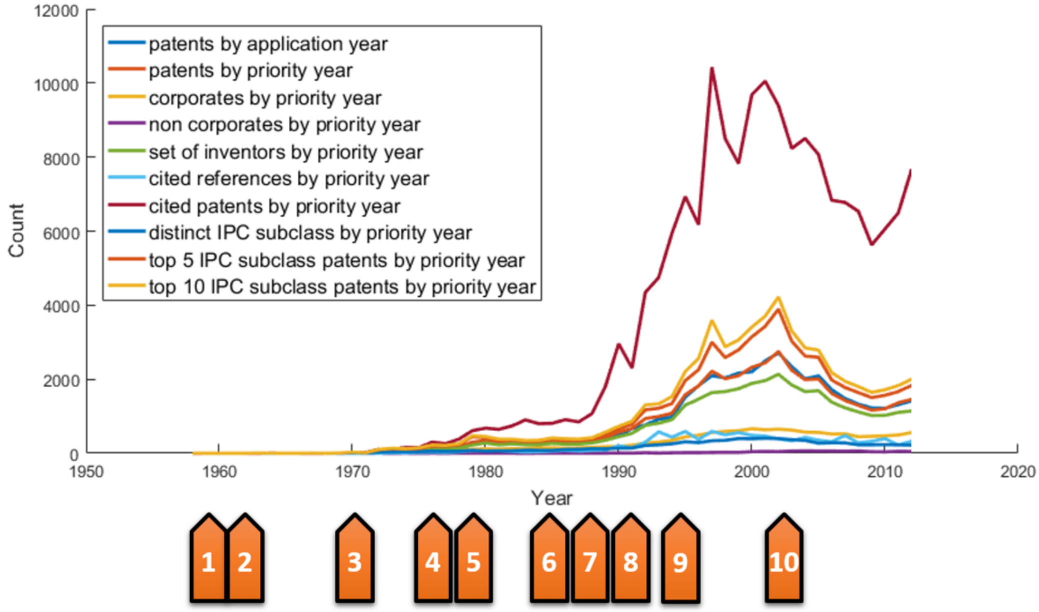


Figure 5.10: Development trends for ink jet printers relative to historical events

5.5.10 The internet

The first patent record in this dataset (GB803431) based on the search terms in Table 5.2 is from 1954 by IBM for a 'Digital electric calculating apparatus', referring to the earliest days of computers and digital communications. Following this, the earliest foundations of the internet can be traced to the work of the Advanced Research Projects Agency (ARPA), a branch of the United States' Department of Defense (DoD) that was established to develop a US lead in science and technology for the military following the USSR's launch of Sputnik in 1957 (label 1 in Fig. 5.11). A period of theoretical development in information flows between networked computers and packet switching technologies occurred between 1961 and 1967, which included an ARPA sponsored study on a "cooperative network of time-sharing computers" that directly linked (without packet switches) MIT's Lincoln Lab TX-2 with the System Development Corporation's AN/FSQ-32 in Santa Monica, California. A third computer from the Digital Equipment Corporation (DEC) was later added to form "The Experimental Network" (label 2). These efforts resulted in publication of the first ARPANET plan and design paper in 1966 and 1967 respectively by Lawrence G. Roberts (label 3). The ARPANET was subsequently commissioned by the DoD for research into networking in 1969, with the first packets sent the same year. This was followed in 1970 by the first publication and implementation of Network Control Protocol (NCP) host-to-host protocols alongside the implementation of the first packet radio network (ALOHAnet), and the invention of an email program for sending messages across a distributed network by Ray Tomlinson of BBN in 1971 (label 4).

By 1973, the first international connections to the ARPANET had taken place from University College London, whilst Vint Cerf and Bob Kahn's publication in 1974 "A Protocol for Packet Network Intercommunication" specified in detail the design of a Transmission Control Program (TCP) (label 5). This was later split into TCP and Internet Protocol (IP) in 1978 (label 6), leading to ARPA adopting the TCP/IP protocol suite and the definition of an "internet" as a connected set of networks in 1982, before transitioning from NCP to TCP/IP on the 1st of January 1983 (label 7). The internet began growing rapidly following the creation of the National Science Foundation Network (NSFNET) in 1986, which provided 5 super-computing centres to supply high-computing power to its users, allowing a sharp increase in the number of connections to take place, particularly from universities (label 8).

At this point the internet remained disjointed, making it difficult to find relevant information. Consequently, Tim Berners-Lee developed the World Wide Web at CERN to make it easier to identify resources through a system of Uniform Resource Locators (URLs), interlinked by hypertext links. This was released to the wider public in 1991 (label 9). This led to the first internet browsers, such as Mosaic, and an explosion of annual internet traffic growth at 341,634% in 1993. Online shopping and retail sites soon arrived in 1994, and early search engines such as BackRub (the predecessor to Google) appeared in 1996 (label 10). The phenomenal growth of the internet continued until the dot-com crash of 2001 when online retail stocks began to tumble. The impact of the Telecom crash on development is seen clearly in Fig. 5.11, similar to the effect observed for fibre optic technologies in Fig. 5.4. The crash was followed swiftly by massive redundancies and the United States' 3rd largest bankruptcy in corporate history when WorldCom Inc. filed for bankruptcy in 2002 (label 11). This situation recovers steadily over the next decade, boosted by the launch of social media sites such as Facebook in 2004 (label 12), and the first decentralised cryptocurrency, Bitcoin, in 2009 (label 13). These new tools have seen incredible growth, with Facebook reporting that over 1 billion users (i.e. 1 in 7 people on Earth) accessed its site during one day in 2015 (label 14).

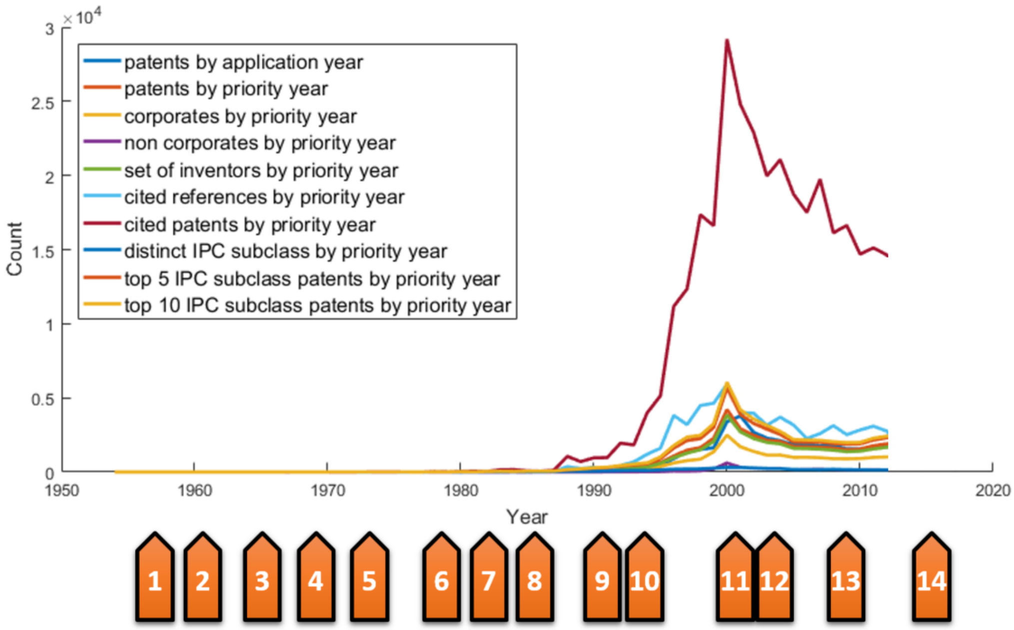


Figure 5.11: Development trends for the internet relative to historical events

5.5.11 Landline telephones

The first patent record in this dataset (US1369288) based on the search terms in Table 5.2 is from 1900 and relates to an automatic telephone exchange. Whilst this record occurs over two decades after Alexander Graham Bell and Elisha Gray filed patents for the telephone in 1876, this occurs in the same year that John W. Atkins made the first international telephone call over telegraph cable between Key West in Florida, and Havana, Cuba, and a year before Guglielmo Marconi transmitted the first transatlantic radio message (label 1 in Fig. 5.12). Rapid technological development and network expansion took place during the first decade of the telephone, and this momentum continued steadily into the early 20th century. This included the development of vacuum tubes by Lee deForest in 1906 (label 2), first transcontinental telephone call (3,600 miles) facilitated by Harold Arnold's vacuum tube amplifier in 1915 (label 3), Ship-to-Shore communication by wire and wireless technologies in 1922 (label 4), and first transatlantic and around-the-world telephone calls in 1926 (label 5) and 1935 (label 6) respectively. In particular, the development of vacuum tube amplifiers, followed by carrier circuits in 1918, led to an accelerated diffusion of the telephone after the First World War. Telephone development continued through the Second World War, but new technologies based on mobile technology also began emerging around this point, leading to the first experimental mobile radiotelephone service in St. Louis, Missouri, in 1946. This was followed in 1947 by the germanium point contact transistor at Bell Telephone Labs, and proposal of using "hexagonal" cells for mobile telephone services (label 7).

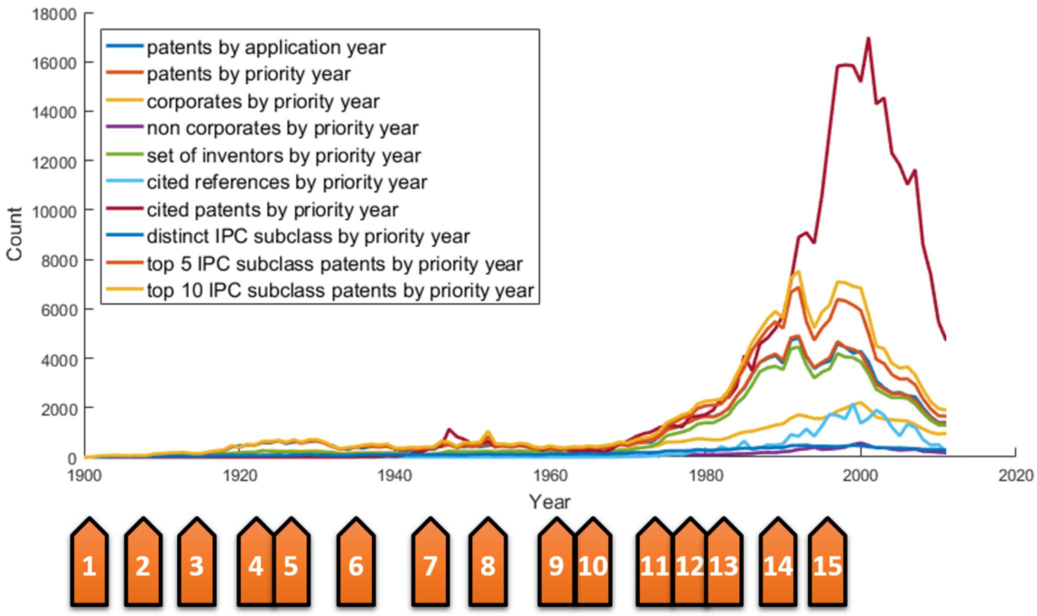


Figure 5.12: Development trends for landline telephones relative to historical events

Mobile phones did not mature for several decades, and consequently wired infrastructure evolutions continued for many years. This included the laying and inauguration of the first transatlantic telephone cable TAT-1 in 1955/1956 (label 8), introduction of the first digital transmission system in 1962 (label 9), first electronic switching system, and first commercial communications satellite (Early Bird, later renamed Intelsat 1) in 1965 (label 10). These events, alongside fibre-optics developments discussed previously, and provision of frequency spectrum for mobile communications in 1968 in the United States, led to much increased bandwidth, coverage, and user proliferation, notably expanding telecommunication developments in the late 1960s. However, following the first hand-held mobile phone call between Motorola and AT&T employees on Motorola's DynaTAC prototype in 1973 (label 11), commercial mobile phone technologies began to emerge, with the first commercial cellular network trialled by Bell Labs in Chicago in 1978 (label 12). Whilst the first smartphone (IBM's Simon) arrived on the market in 1994, there were already 33.8 million wireless subscribers in the United States by 1995, representing 13% of the population. Wired telephones began to fade from use around 1997 as mobile phones grew in popularity (label 15). Following the Telecom collapse of 2001, mobile technology developments have taken precedence and largely replaced wired systems.

5.5.12 Laser printers

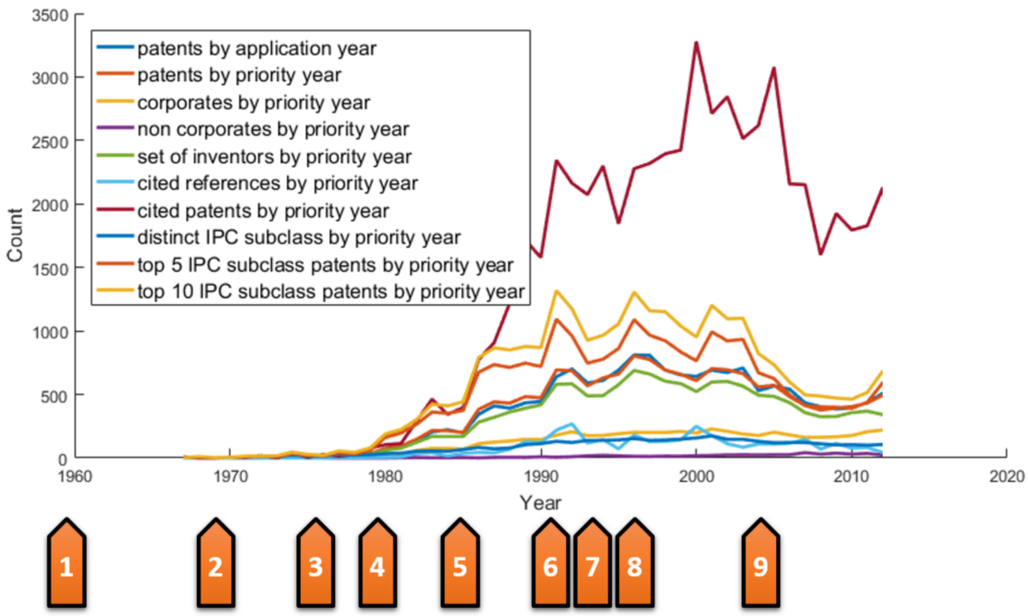


Figure 5.13: Development trends for laser printers relative to historical events

The first patent record in this dataset (US3410203) based on the search terms in Table 5.2 is from 1967 and describes a potential laser printer mechanism. Two years later, Gary Starkweather at Xerox demonstrated using a laser beam with the xerography process to create a laser printer (label 2 in Fig. 5.13), the basic principles having been established by the firm's prototype Xerographic copier (the 'Model A') in 1949, and subsequently validated by their launch of the first commercially successful plain paper copier, (the Xerox 914) in 1959 (label 1). The first laser printers were then commercialised in 1975 and 1976 with the Xerox 9700 and the IBM 3800 respectively (label 3). These were prohibitively expensive, and so initially limited to applications such as cheque printing, but the IBM 3800's ability to print over 20,000 lines per minute demonstrates the future versatility. As such, in 1979 Canon introduced the first lower-cost desktop laser printer, the LBP-10, which attracted commercial interest from businesses, and encouraged further technical development (label 4). This was considerably cheaper than its predecessors, but not yet affordable for consumer markets, which subsequently took-off with HP's 300 dpi resolution LaserJet printer in 1984 (label 5). This coincided with the launch of the Apple Macintosh and desktop publishing the following year when PageMaker was released for the Apple LaserWriter. Mass-market sales began in 1990 with the release of HP's LaserJet IIP, which broke the $1,000 price barrier for the first time (label 6), followed by the first colour laser printer (QMS ColorScript Laser 1000) in 1993 (label 7). As with inkjet printers, affordable photo-quality laser printers appeared on the market around 1996 (label 8), but sales again declined in the mid-2000s as mobile technologies reduced the need for desktop printing (label 9).

5.5.13 Light-emitting diode (LED) lights

The first patent record in this dataset (US2546190) based on the search terms in Table 5.2 is from 1946, describing a housing and light diffuser for fluorescent lights, similar to those used in modern LED screen backlights. This was followed by a patent with priority in 1952 for an 'electroluminescent oscillator' (US2626346), which preceded Nick Holonyak Jr.'s first practical visible-spectrum light-emitting diode (LED) in 1962 (label 1 in Fig. 5.14). However, it was not until around 1990 that high-brightness red, orange, yellow, and green LEDs were introduced (label 2), and two years later for Nichia Labs to develop a visible blue and green LED that attained 10% efficiency (label 3). This was crucial for white LED lighting, and led to Shuji Nakamura inventing the first high-brightness blue, and with additional Phosphor, white LEDs at Nichia in 1995, instigating major growth in LED development (label 4). In the ensuing years LED lighting would first equal incandescent efficacy of 17 lumens per watt in 2000 (label 5), and fluorescent bulb efficacy of 70 lumens per watt in 2005 (label 6). As of 2017, Philips has begun producing LED bulbs achieving 200 lumens per watt, defying U.S. Department of Energy predictions that this barrier would only be passed around 2025 (label 8).

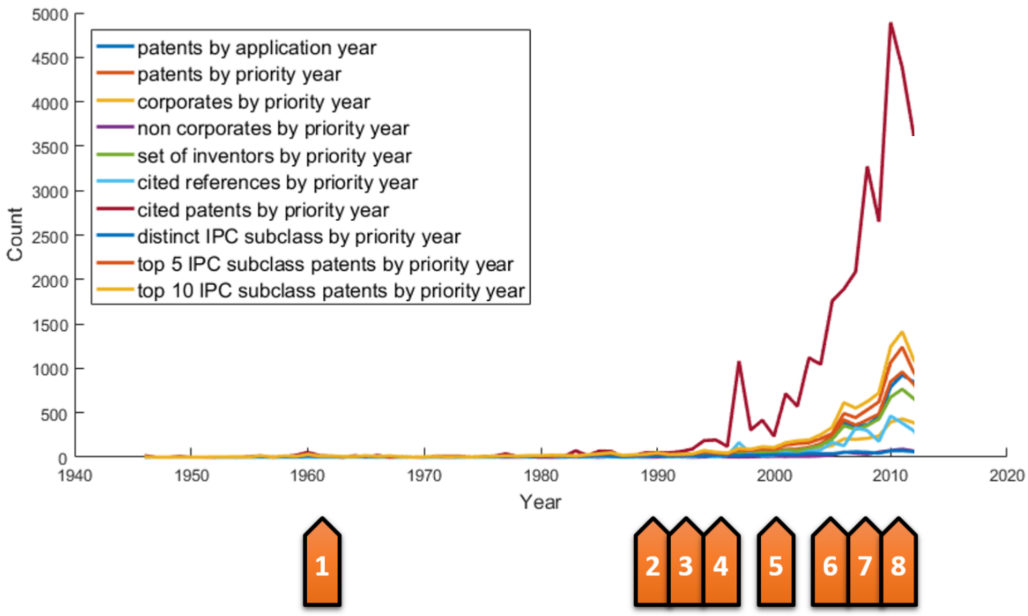


Figure 5.14: Development trends for LED lights relative to historical events

5.5.14 Linear Fluorescent Tube (LFT) lights

The first patent record in this dataset (GB249713) based on the search terms in Table 5.2 is from 1925 and relates to using fluorescents to create a luminous disk, in the same year that internal frosted light bulbs are first produced, and a year before Edmund Germer's files a patent for a fluorescent lamp (label 1 in Fig. 5.15). The milestones listed for CFLs are naturally of equal significance here (see section 5.5.1). Additionally the development of Halophosphor Linear Fluorescent Tubes (LFTs) in 1948 (label 4), introduction of T8 LFTs in 1978 (label 6), Philips' use of new rare earth phosphors that emit warmer colour and increased light output in 1982 (label 7), and introduction of T5 LFTs with cool tips that achieved an efficacy of 117 lumens per watt in 1994 (label 9) were also significant for LFTs.

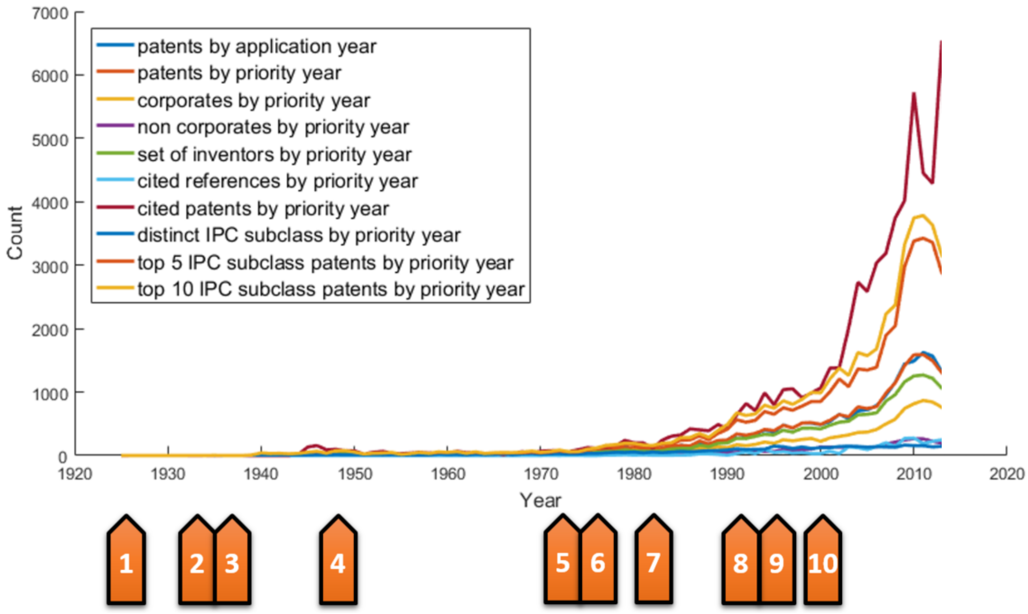


Figure 5.15: Development trends for LFT lights relative to historical events

5.5.15 Nuclear energy

The first patent record in this dataset (US737) based on the search terms in Table 5.2 is from 1838 and relates to the manufacture of knives and forks from a single piece of sheet steel, before then having metal cast around them to encase them. This metal-on-metal casting technique related to both the fabrication of nuclear fuel itself (with earlier techniques encasing uranium metal within metal sheaths [Beck, 1994, Stephenson, 1959]), and encasing nuclear waste in metal alloys for storage and disposal [Glasstone and Sesonske, 1994]. This was followed by the development of non-conducting sheaths for steam boilers in the 1860s. However, the bulk of nuclear energy developments began in the late 1890s, with the discovery of X-rays in 1895 by Wilhelm Roentgen, electrons in 1897 by J. J. Thomson, radioactive elements radium and polonium in 1898 by Marie Curie, and Rutherford's observation of two different types of rays emitting from radium in 1899 (label 1 in Fig. 5.16). This continued into the early 1900s with Frederick Soddy's observation of isotopes in 1900, Rutherford's publication on the theory of radioactive decay in 1901, Einstein's publication of the special theory of relativity in 1905 (label 2), and Rutherford's discovery of the atomic nucleus in 1911 (label 3). This was followed in 1919 by the creation of the first artificially induced nuclear reaction, when Rutherford bombarded nitrogen gas with alpha radiation (label 4).

The next major theoretical steps were taken as James Chadwick discovered the neutron in 1932, the same year that John Cockcroft and Ernest Walton split lithium atoms with protons accelerated in their 'linear accelerator'. Enrico Fermi subsequently achieved the world's first nuclear fission from uranium in 1934 (label 5). Einstein described the possibility of a uranium weapon to President Roosevelt in 1939, leading to nuclear fission becoming a critical strategic concern for the United States and allies as weapon development efforts advanced in Germany during World War II (label 6). Consequently, the Manhattan Project was formed in 1942 to allow the United States to develop the first atomic bomb, building on the first self-sustaining, controlled, nuclear chain reaction achieved by Enrico Fermi at the University of Chicago in the same year. This ultimately resulted in the detonation of the first nuclear weapon, code-named Trinity, in New Mexico in 1945, prior to the destruction of Hiroshima and Nagasaki in Japan to bring about the end of World War II.

Soon after, the Atomic Energy Act (AEA) of 1946 was passed by the U.S. Congress to explore peaceful uses of nuclear energy (label 7). From this, an experimental breeder reactor was constructed and began operation in Idaho in 1951, delivering the first usable electric power, followed by the first Boiling Reactor Experiment and nuclear-powered submarine (the U.S.S. Nautilus) in 1953. At the same time, Eisenhower's 'Atoms for Peace' program proposed an international agency to develop peaceful nuclear technologies (label 8). Development accelerated in the second half of the 1950s, with the world's first commercial nuclear power station, Calder Hall, opening at Windscale (UK) in 1956, followed by the Soviet Union launching the first nuclear-powered surface ship (the 'Lenin') in 1957. The first major concerns about nuclear power also became apparent during this year, as the Windscale fire of the 10th of October caused one of the first major nuclear accidents (label 9).

Nuclear energy developments again received a significant boost in 1973 following the "Yom Kippur" war and ensuing OPEC oil embargo (label 10). The partial meltdown at Three Mile Island in 1979 led to a significant investment in emergency response planning, reactor operator training, human factors engineering, and radiation protection, amongst many other changes implemented in nuclear reactor design and operation (label 11). Conversely, nuclear technology development suffered significantly following the catastrophic meltdown at Chernobyl on April the 26th, 1986, as opposition to nuclear power generation became paralysing for many governments (label 12). Gradually, this situation began to improve once again, and in 1996 Japan inaugurated the world's first Advanced Boiling Water Reactor (label 13). Meanwhile, the United States launched the 'Nuclear Power 2010 Program' in 2002 to develop and bring to market advanced nuclear generation technologies, whilst examining the feasibility of new nuclear plants (label 14). The renewed nuclear development activities have again been called into question more recently following the 2011 Fukushima Power Plant disaster, which was the most significant incident since Chernobyl, and only the second disaster to be given the Level 7 event classification on the International Nuclear Event Scale (label 15).

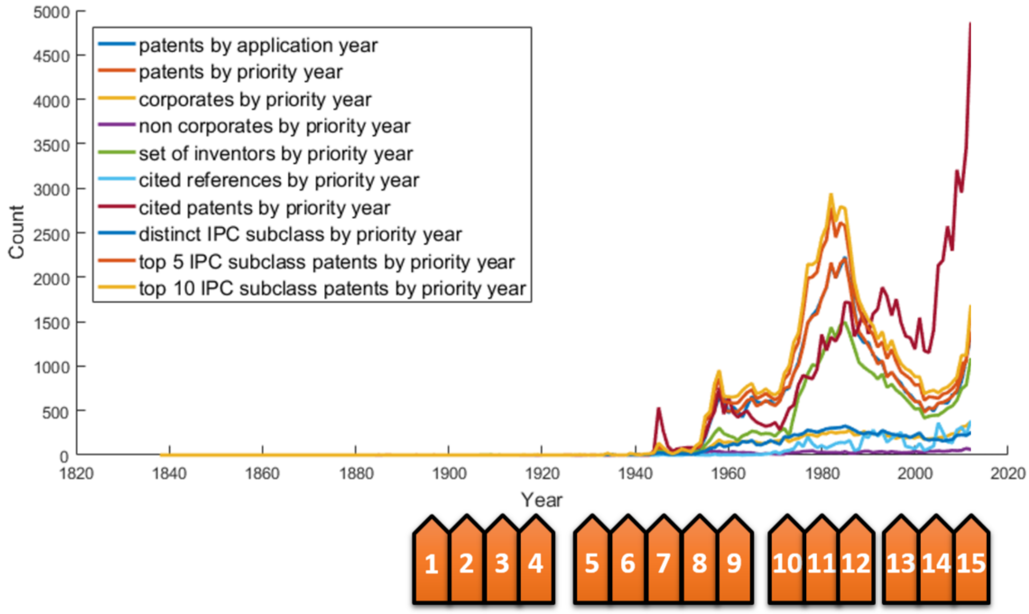


Figure 5.16: Development trends for nuclear energy relative to historical events

5.5.16 Solar photovoltaics

The first patent record in this dataset (AT25139) based on the search terms in Table 5.2 is from 1904 and describes the use of semiconductors, fluctuating voltages, and accumulator batteries within an electrical lighting system. In the same year, Wilhelm Hallwachs discovered that a combination of copper and cuprous oxide was sensitive to light, leading to creation of a semiconductor-junction solar cell, and Einstein published his paper on light and electrons that first described the photoelectric relationship on a quantum basis (label 1 in Fig. 5.17). The earliest patent for a solar cell was actually from Edward Weston in 1888, but these records are not captured in the FamPat database. Solar photovoltaic (PV) development continued through the first half of the 20th century, with the discovery of methods for producing single-crystal silicon in 1918 (label 2), the photovoltaic effect in Cadmium Selenide (CdSe) in 1932 (label 3), and single-crystal germanium in 1948 (label 4). However, these earliest solar cells were very inefficient, and it was not until 1954 that a practical solar cell with an efficiency of 6% was achieved by Daryl Chapin, Calvin Fuller, and Gerald Pearson at Bell Labs (label 5). This led to steadily improving solar cell efficiencies at Hoffman Electronics in the late 1950s (label 6), and solar cells powering the Telstar communications satellite in 1962 (label 7).

Like the other renewable energy technologies discussed so far, solar PV development grew steadily following the 1973 oil embargo (label 8). The University of Delaware demonstrated 'Solar One' during this period, the world's first PV-powered houses coupled with flat-plate thermal collector heating systems, whilst the Solar Energy Industries Association (SEIA) was formed in the United States in 1974. This was followed by the foundation of the U.S. Solar Energy Research Institute (SERI - later renamed the National Renewable Energy Laboratory) in 1977, the mandated purchase of electricity from efficient energy sources under the PURPA legislation of 1978, and substantial tax credit and investment incentives over the following 10 years (label 9). Further assistance was provided for residential PV applications through the 1980 'Crude Oil Windfall Profit Tax Act', and an additional 25% tax credit in California, whilst the first thin-film solar PV cells with efficiencies greater than 10% were developed by Boeing, Kodak, and the University of Delaware (label 10).

Major government residential installations begin in 1990 with the '1,000 Solar Roofs Program' in Germany, accompanied by an innovative feed-in tariff scheme (label 11). This inspired the '100,000 Solar Roofs Program' in 1999 with technology-dependent feed-in tariffs (label 13), and most recently the 'One Million Solar Roofs by 2017' program launched by California Governor Arnold Schwarzenegger in 2004 (label 14). In the meantime, solar cells broke the 40% efficient sunlight-to-electricity barrier in 2006. In 2011, rapidly expanding factories in China significantly reduced solar panel manufacturing costs, bringing prices down to around $1.25 per watt for PV modules. This leads to a doubling of installations worldwide (label 15). Most recently, Tesla completed its first solar roof installations in August 2017, bringing a new module design and entry price that is targeted at mass-market adoption (label 16).

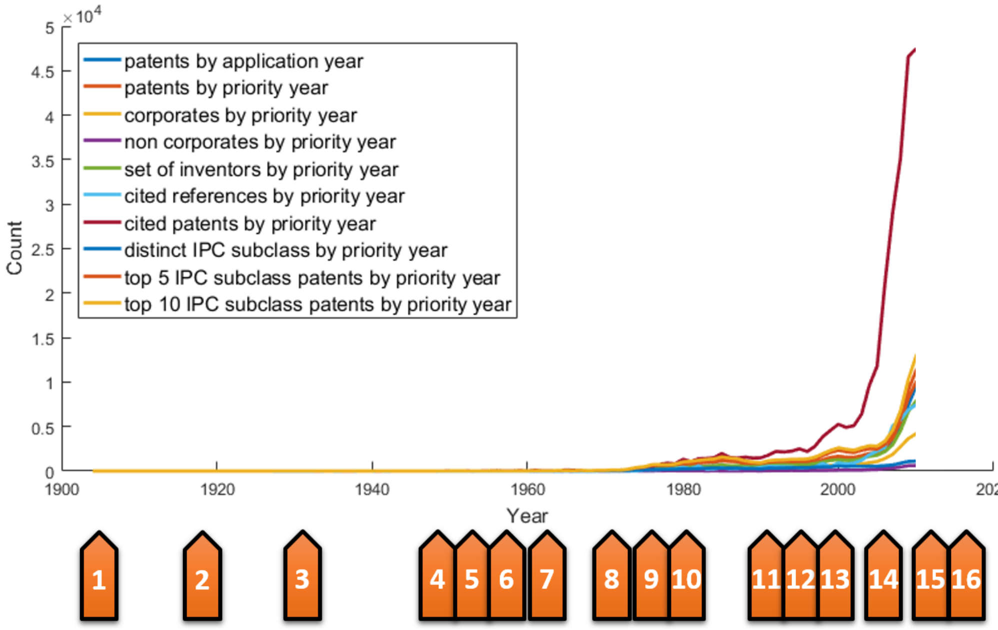


Figure 5.17: Development trends for solar PV relative to historical events

5.5.17 Solar thermal electricity

The first patent record in this dataset (US31639) based on the search terms in Table 5.2 is from 1861, for an adjustable mirror that focused sunlight onto a central point of a camera. This takes place a year after Auguste Mouchout, a French mathematics teacher, began experimenting with solar cooking, culminating in a small solar powered steam engine (label 1 in Fig. 5.18). Mouchout followed this by inventing the first parabolic trough solar collector in 1866. A decade later in 1878 William Adams constructed a reflector made of flat-silvered mirrors arranged in a semicircle focused on a stationary central boiler, which tracked the sun by rolling around a semicircular track (label 2). This was followed between 1883 and 1884 by John Ericsson's creation of a solar engine that used a parabolic trough arrangement (label 3). However at this time, coal was the abundant power source supplying the world's growing industries (with limited knowledge of environmental impacts), so interest in using solar collectors for commercial applications was low. Consequently, it was not until the 1920s that solar water heating systems employing flat-plate collectors were adapted to supply homes and apartment buildings in Florida and Southern California (label 4). By 1956, the world's first commercial solar building (using a south-facing glass wall alongside mechanical and passive solar technologies) was designed and erected by Don Paxton and Frank Bridgers in Albuquerque, achieving high efficiency through solar heating and thermal storage, and providing the template for modern energy-efficient premises (label 5).

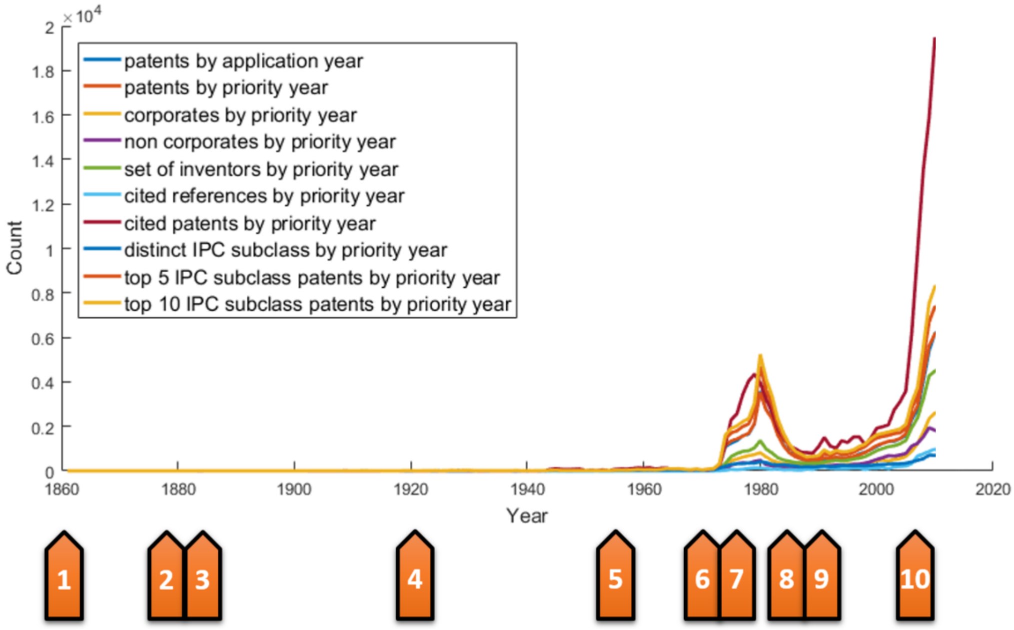


Figure 5.18: Development trends for solar thermal relative to historical events

Serious commercialisation efforts, however, were inspired by the creation of an eight-story tall parabolic 'solar furnace' constructed in Odeillo, France in 1969 (label 6), and the 1973 oil embargo (label 7). Many of the same organisations, incentives, and subsidies described for solar PV systems were equally applicable to solar thermal in the late 1970s. By contrast, solar thermal technologies suffered more notably from low oil prices between 1986 and 2000, although major technical developments were still made in the early and mid-1980s. This began with construction in 1982 of 'Solar One' (not to be confused with the previous solar PV-hybrid house of the same name); a 10 MW central receiver demonstration, commonly known as a solar tower, that proved the feasibility of power tower systems, and achieved an availability of 96% in its final year of operation. The next year, the first in a series of Solar Electric Generating Stations (SEGS) was installed, providing 13.8 MW through solar trough technologies coupled with a conventional steam turbine generator. This was followed in 1984 by Advanco and McDonnell Douglas' demonstration of high-efficiency solar dishes, and approval for construction of the world's largest solar thermal facility at Kramer Junction in 1986 (label 8). In 1989, advanced hybrid systems appeared, with the combination of reflective solar concentrators and PV cells, whilst the U.S. government modified regulations to increase the maximum allowable solar plant size (label 9). This led to renewed growth in solar thermal development, enabling connection of the first solar dish generator using a free-piston Stirling engine to a utility grid in 1994, and later, the approval of the California Solar Initiative (CSI) in 2006, providing $2.8 billion of funding for solar technologies over 11 years (label 10).

5.5.18 Thin-film-transistor liquid-crystal displays (TFT-LCD)

The first patent record in this dataset (US3824003) based on the search terms in Table 5.2 is from 1973 and describes a liquid-crystal display panel that uses thin-film-transistor technology. However, the first working liquid-crystal display (LCD) was built by George H. Heilmeier in 1964, with the first active-matrix LCD panel produced by Westinghouse in 1972 (label 1 in Fig. 5.19). The major catalysts for this were the invention of twisted-nematic mode of LCD in 1971, and synthesis of cyanbiphenyl liquid-crystal material at Hull University in 1972. Technical development grew steadily after the world's first LCD TV watch was introduced in 1982, and by 1988 Sharp Corporation had developed the first 14-inch colour TFT-LCD TV, known as the Crystaltron (label 2). The first public digital high-definition television broadcasts in the United States and Europe, in 1996 (label 3) and 2004 respectively, further accelerated advances in LCD screens, until LCD televisions surpassed Plasma in popularity in around 2007 due to their large size and lower costs (label 4). However, LED and OLED technologies also continued to improve, with LCDs becoming a mature technology in their own right. More recent technical developments have therefore shifted their focus to LED and backlight technologies, including the introduction of quantum-dot technology in 2013 (label 5).

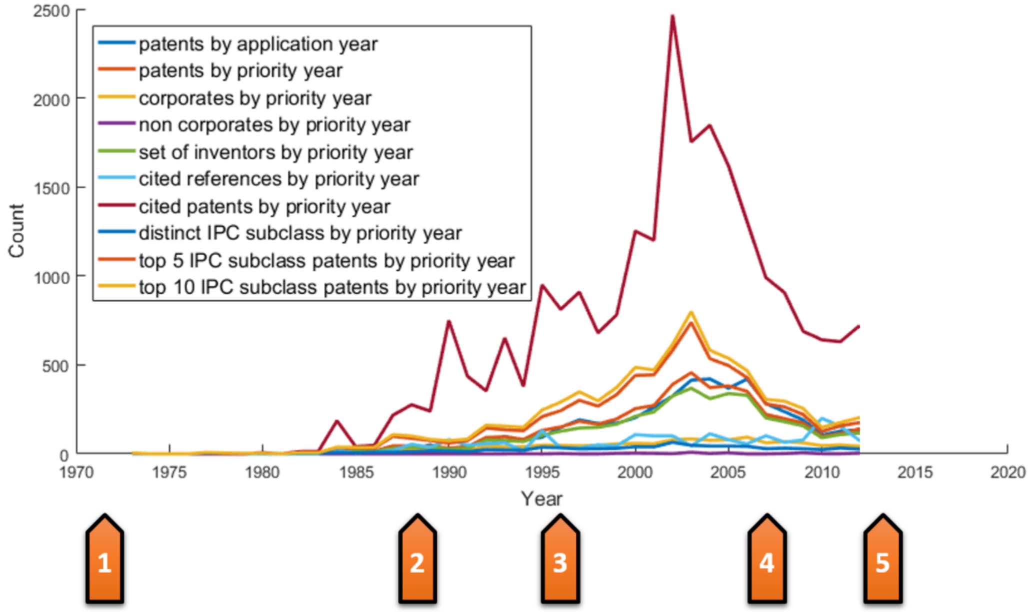


Figure 5.19: Development trends for TFT-LCD relative to historical events

5.5.19 Thermal printers

The first patent record in this dataset (US2917996) based on the search terms in Table 5.2 is from 1955 and describes a thermal printer design to improve the speed of existing impact-based printers (where inertia of impact hammers limited printing speeds). Experimentation with thermal methods for transferring images took place around this time, with the dye-sublimation process developed in 1957 (label 1 in Fig. 5.20), whilst the idea of treating paper rather than applying ink to untreated paper was bolstered by Gerber Scientific's development of photoplotters in the 1960s (label 2). However, direct thermal printing only became a reality in the 1970s when they were provided with microcomputer systems, such as the Atari 822 for 8-bit Atari systems and the Alphacom 32 for Sinclair ZX Spectrum (label 3). The development of thermal wax printers (also known as thermal transfer printing) in 1982 led to increased commercial interest for label printing (label 4). Whilst this relied on a heat-sensitive ribbon instead of heat-sensitive paper, similar thermal print heads were used. During the 1990s, thermal printing was employed in many fax machines. However, the rapid development of inkjet and laser printers, which began to overtake demand for impact printers after 1991 (label 5), meant that by the early 2000s thermal printing had largely been replaced in fax machines. Despite this, the favourable energy consumption and small lightweight size have meant that thermal printers have remained popular for portable devices and retail applications. As with previous printing technologies discussed, an observable impact occurs in the mid-2000s as cloud storage and mobile technologies reduce demand for consumer printing technologies (label 6).

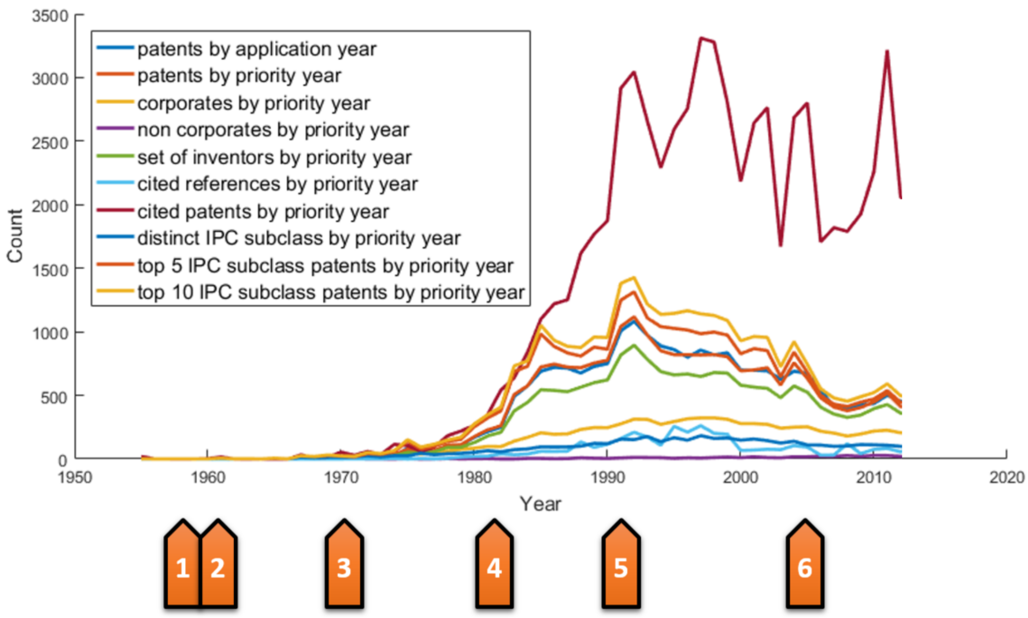


Figure 5.20: Development trends for thermal printers relative to historical events

5.5.20 Tide, wave, and ocean-based electricity generation

The first patent record in this dataset (US1478) based on the search terms in Table 5.2 is from 1840 and describes the design of an improved tide or current wheel that allowed water buckets to close when rotating against the direction of the current, reducing the mechanism's overall resistance. Whilst the first patent regarding wave-energy was in 1799 from Pierre Girard (France), consideration of tidal flows dates back to references in Greece from the time of Aristotle. Jules Verne provided insight into how tidal energy may be harvested in his novel *20,000 Leagues under the Sea*, where fictional Captain Nemo describes using thermoelectricity from ocean water (label 1 in Fig. 5.21). The concept of ocean thermal energy conversion (OTEC) was then proposed in more detail by Jacques Arsene D'Arsonval in 1881 (label 2). It would take nearly 30 years for the first wave power technologies to be developed, with Bochaux Praceique's oscillating water-column wave-energy device lighting and powering his house in Royan, near Bordeaux, in 1910 (label 3). Despite the testing of open-cycle OTEC processes in Cuba in 1934, a series of tidal power station studies in the Bay of Fundy between 1935 and 1977 (label 4), Yoshio Masuda's pioneering of modern wave energy and extraction of power from the angular motion of articulated rafts in the 1940s (label 5) and 1950s (label 6) respectively, commercial applications remained rare until the late 1950s. At this point, small tidal plants (< 1 MW_e) were reportedly used in China in 1959 (label 7). Several years later, the Rance River tidal power plant became operational in France in 1966 (label 8).

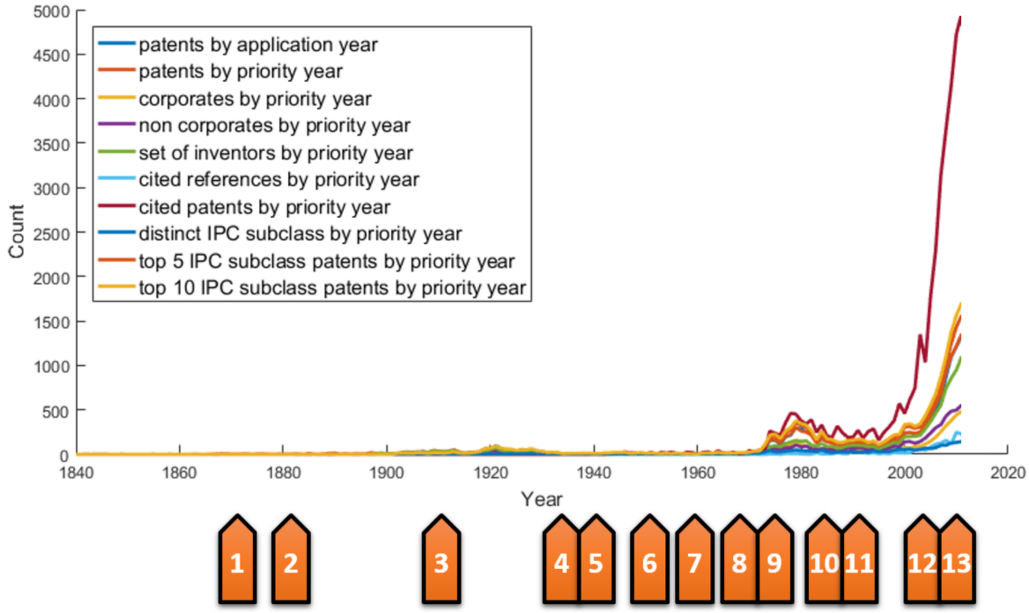


Figure 5.21: Development trends for tide, wave, and ocean electricity generation relative to historical events

Tide, wave, and ocean power generation technologies all benefited following the oil crisis, although the U.S. OTEC program began prior to this in 1972, followed by the British wave-power program from 1976 to 1982 (later reinstated post-2000). During this period, considerable advances were made. These included Stephen Salter's 'nodding duck' (a.k.a. Edinburgh Duck) in 1974 which demonstrated an 81% efficiency in converting wave motion to electricity, Alan Wells' 1977 invention of a turbine that rotates in one direction irrespective of the direction of fluid flow, installation in 1978 of a 125 kW wave-power unit off Honshu in Japan, and operation of mini-OTEC plants by the U.S. and Japanese in 1979 (label 9). This period of activity culminated in the opening in 1984 of the 20 MW Annapolis tidal station in

Nova Scotia (label 10). Shortly afterwards, declining fossil fuel prices began to sap interest from more expensive categories of renewable energy, which proved significant for developments out at sea (label 11). As oil prices escalated again after 2000, the European Marine Energy Centre was established in the Orkney Islands as the world's first marine energy test facility (label 12). In 2007, this resurgence in marine energy brought Pelamis devices into commercial operation, whilst the first underwater tidal stream turbines were installed in New York's East River (label 13).

5.5.21 Turbojets and jet propulsion

The first patent record in this dataset (CH33261) based on the search terms in Table 5.2 is from 1905 and relates to improvements in gas turbine design. This occurs after the modern steam turbine was invented by Sir Charles Parson in 1884, and Sanford Alexander Moss' paper published in 1900 on turbocompressors (label 1 in Fig. 5.22). Moss follows up on his paper by building and operating a turbocompressor testbed in 1903, the same year that Ægidius Elling built a gas turbine that ran under its own power, often considered the first working gas turbine (label 2). However, it is not until 1917 that Moss began developing turbochargers further at General Electric, prior to GE opening their gas turbine division in 1918, which supports development efforts over the next decade (label 3). In parallel, James Stocker Harris patents a 'Motor Jet' design for his brother-in-law Robert Alexander Raveau Bolton in 1917. Interest temporarily stalls following a report by W. J. Stern to the Royal Air Force in 1920 that predicted no future for turbine engines in aircraft, based on the extremely low efficiencies of compressors at the time. This was countered in 1926 by a paper from Alan Arnold Griffith, demonstrating that the low efficiencies observed resulted from the current generation of compressors effectively 'flying stalled', and illustrating mathematically how a practical engine (in this case a turboprop) could be a reality (label 4).

With interest revived, Frank Whittle considers the need for high-speed flight, and the impending obstacle of propeller efficiency to further speed advances in his 1929 thesis on the future of aircraft design. The following year, Whittle presented a complete jet engine design to the Air Ministry. Griffiths noted the low efficiency of Whittle's current design and dismisses the use of a centrifugal compressor as impractical, resulting in the ministry rejecting the proposal. Whittle continues, encouraged by friends in the Royal Air Force, and patents his engine in 1930 (label 5). Hans von Ohain's thesis at the University of Göttingen in 1933 describes, independently, a similar engine concept to Whittle's design, except using a centrifugal fan as the turbine as well as the compressor. Although this design did not progress, Ohain and Max Hahn patented a new design in 1936. Meanwhile, after founding Power Jets Ltd in 1935, Whittle's experimental centrifugal engine was tested at the Thomson-Houston plant in Rugby in 1937. In 1938, Ohain and Hahn, now working at Heinkel, tested the first aircraft-ready jet engine (the HeS 3) in a testbed. This engine was subsequently fitted to a Heinkel He 118, making this the first aircraft to be powered by (although not designed around) jet power alone (label 6).

Turbojet development greatly accelerated as World War II began. The Air Ministry was impressed to observe a jet engine running continuously at full power for 20 minutes at Power Jets, and requested Whittle to develop a flyable version. Production contracts were offered to most UK engine manufacturers, before the Air Ministry contracted Gloster Aircraft Company to build an experimental airframe. Consequently, in May 1941, the Gloster E.28/39 flew for the first time using Whittle's W.1X engine (making this the third specifically designed jet aircraft to fly after the Heinkel 178 and the Caproni Campini N.1), but quickly overtakes the top speed of any existing propeller aircraft in the weeks that followed (label 7). As the war progressed, the underlying technology matured and both sides targeted full scale strategic and tactical deployment. As such, a Power Jets W.2B was supplied to GE in the U.S. in October 1941 to start production (assisted by Sanford Alexander Moss), the Messerschmitt Me 262 became the first jet-powered fighter aircraft in July 1942 (entering combat service in April 1944), the first running turbofan was tested by Daimler-Benz in April 1943, and the Gloster Meteor entered squadron service with the Royal Air Force in July 1944. By the end of the war, a Derwent V powered Meteor had achieved a world speed record of 606 mph, signalling the dominance of this new propulsion system.

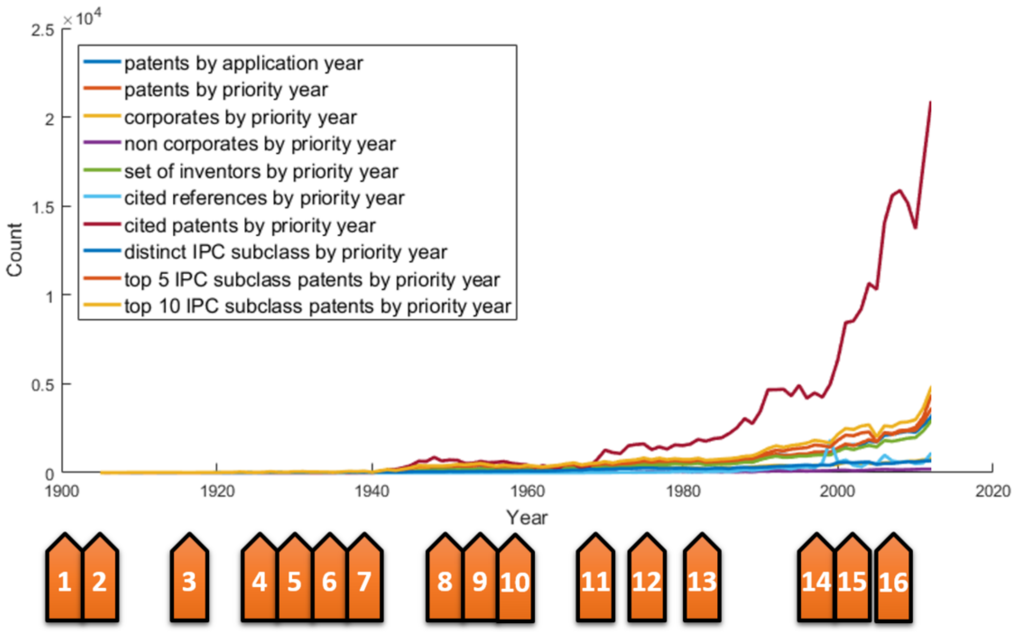


Figure 5.22: Development trends for turbojets relative to historical events

Whilst technical advances continued after the war, such as breaking the sound barrier in 1948 using rocket propulsion, focus also shifted to commercial applications. Turbojets were deployed commercially in 1949 with the De Havilland Comet 1 prototype, which was powered by the first non-military axial flow jet engine, the Rolls-Royce Avon (label 8), before entering service with the British Overseas Airways Corporation (BOAC) in 1952 (label 9). The commercial success of the Jet Age arguably began with the Boeing 707, which entered service with Pan American in October 1958 (label 10). By this point increases in the top speed of jet engines in military combat aircraft had again largely stalled (see Appendix E of Chang and Baek [2010]). Commercial aircraft, however, achieved significant technical milestones with the first flight of Concorde in 1969 (label 11), and in 1975 entry into service of the world's first supersonic jetliner, the Russian Tu-144S (label 12). Beyond this point, engine development focused more on improving fuel burn efficiency and environmental performance, although recent investment in experimental scramjets has resulted in the successful demonstration of the Hyshot scramjet in 2002 (label 15), and the first scramjet to attain Mach 10 in 2007 (label 16).

5.5.22 Wind electricity generation

The first patent record in this dataset (US479) based on the search terms in Table 5.2 is from 1837 for a free-standing windmill, separated from other buildings (although transferring power by pulleys, shafts and belts to any machines within), that rotated on a circular track to orientate its vanes according to wind direction. This record appears over a decade before Daniel Halladay and John Burnham started the U.S. Wind Engine Company in the 1850s and designed the Halladay Windmill for the American West (label 1 in Fig. 5.23). More direct power generation attempts would not occur until the late 1880s, with the advance of steel blades on windmills (increasing efficiency), Thomas O. Perry's wind experiments determining best mathematical principles for windmill design, and the first electricity generating windmills constructed by Professor James Blyth in Glasgow and Charles F. Brush in Cleveland in 1887 and 1888 respectively (label 2). The Danish scientist Poul la Cour continued this work in 1891 by building his own wind turbine to generate electricity, hydrogen (via electrolysis), and lighting for Askov school. Cour developed the first regulator to maintain a steady supply of power, and converted his windmill into a prototype power plant to light the rest of Askov village in 1895 (label 3).

The first attempt at commercial scale production of wind turbine generators began in 1927 when Joe and Marcellus Jacobs opened the Jacobs Wind factory in Minneapolis, providing generators for farm use (label 4). This was followed by the Darrieus wind turbine in 1931. This vertical axis design allows wind to be captured from any direction without adjustment, and the heavy generator and gearbox to be secured to the ground instead of on top of a tower, although this restricts these turbines to slower air flows. However, a U.S. rural electrification project launched in 1936 removed much of the natural demand for wind-generated power (label 5). As such, the motivation for developing wind turbines was lost, resulting in most U.S. windmill companies going out of business in the 1950s (label 7). The exception to this was during the Second World War, when the first wind turbine prototype greater than 1 MW provided power to the community at 'Grandpa's Knob' for several months after Palmer Putnam enlisted GE (who had previously bought out the Brush Electric Co.) to trial the technology (label 6).

Following several mechanical failures of the Smith-Putnam wind turbine, leading to its eventual abandonment, serious attempts at wind power generation were not re-attempted until the 1973 oil crisis. This inspired the U.S. National Science Foundation, Department of Energy (DOE), and NASA to launch a research program into increasing wind power technology from 1974 to 1982 (label 8). This resulted in significant advances in wind turbine technology, although the first multi-megawatt turbine was actually constructed by teachers and students at Tvind school in Denmark (label 9). Although U.S. government incentives such as PURPA, Crude Oil Windfall Profits Tax Act, and California's renewable favoured contract system enacted in 1983 continued momentum for wind turbine development in the early 1980s, U.S. DOE funding for wind power reached its lowest level in 1989 as fossil fuels became cheaper (label 10). This lack of enthusiasm was reversed in the early 1990s with the U.S. Energy Policy Act of 1992 mandating increased energy efficiency, development of some of the first commercially viable variable-speed wind turbines by U.S. Windpower in 1993, and reduction in technology costs resulting from the DOE's 1995 Wind Energy Program (label 11). Similarly, the United States' Energy Policy Act of 2005 reinforced this resurgence (label 12). However, in terms of technical advances, the inauguration of 'Hywind' in the North Sea in 2009, the first operational deep-water large-capacity floating wind turbine, marked a significant achievement in pushing wind turbines beyond their conventional operating constraints (label 13).

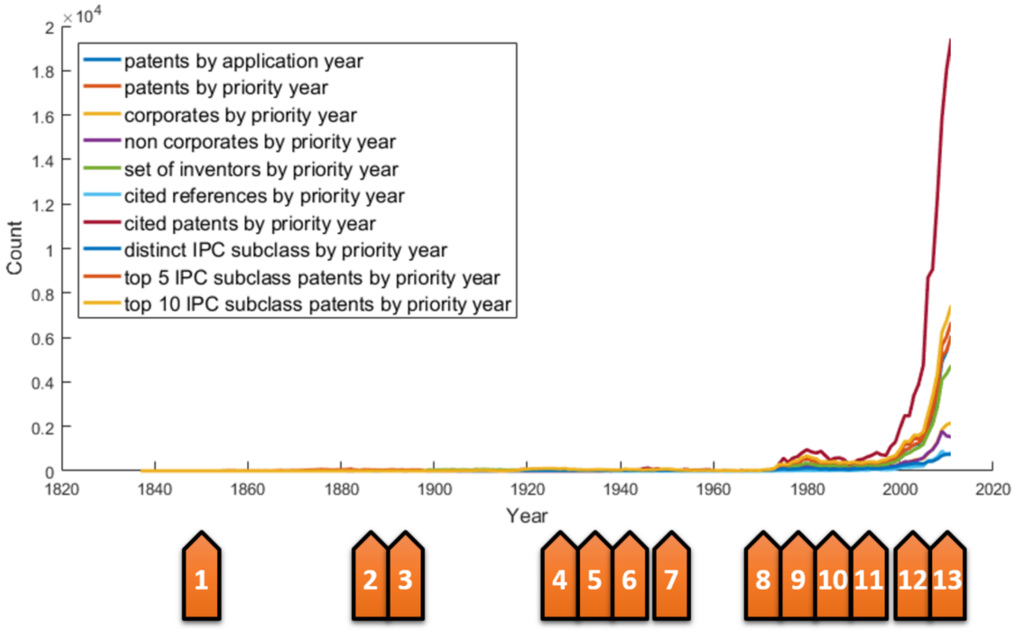


Figure 5.23: Development trends for wind energy relative to historical events

5.5.23 Wireless data transfer

The first patent record in this dataset (US4597067) based on the search terms in Table 5.2 is from 1984 and describes the digital transmission of data between a solenoid and remote receiver using audible binary pulses, for sensing hole parameters in drilling. This illustrates one of the many uses of wireless packet switching technologies. However, the first public demonstration of wireless packet data networks actually occurred when ALOHAnet and the ALOHA protocol, developed by the University of Hawaii, became operational in June 1971. The most easily observable use of wireless data transfer has subsequently come from mobile phones, with advances in mobile phone technology often closely associated with developments in wireless data applications. As such, 1983 marked an important year for wireless data transfer as Motorola introduced the DynaTAC mobile radiotelephone, whilst the first commercial cellular system began operation in Chicago (label 1 in Fig. 5.24). This coincided with the switch-over to TCP/IP as the official protocol for ARPANET, which was important as the internet formed the other ingredient critical to advancing wireless data transfer.

The United States Federal Communication Commission (FCC) chose not to mandate specific standards for cellular radio in 1988, instead adopting a flexible approach that supported the introduction of advanced cellular technologies by industry. Consequently the 'technology wars' began in 1989 for competing digital cellular standards, with wireless technologies evolving simultaneously (label 2). In the early 1990s mobile phone usage expanded significantly, passing 10 million subscribers in 1992. The same year, the world's first commercial text message was sent by employees of Logica CMG. Additionally, Australian radio astronomers led by Dr John O'Sullivan filed a key patent used in Wi-Fi following a failed experiment to detect mini black holes, and were later credited with inventing Wi-Fi. The following year, the U.S. Congress established a national framework for wireless regulation and authorised the FCC to auction radio spectrum, coinciding with the launch of the first smartphone, the IBM Simon (label 3). This accelerated wireless data transfer progress. Development efforts were further reinforced by the U.S. Telecommunications Act of 1996 (intended to open up other communication markets to competition), the release of the IEEE standard 802.11 protocol for wireless local area networking in 1997 (label 4), and the foundation of the Wi-Fi alliance in 1999 (label 5). By 2000, digital wireless users outnumbered analog subscribers, and by 2005 Wi-Fi reached maturity with over 100 million Wi-Fi chipsets sold annually (label 6). The launch of the iPhone in 2007 and iTunes in 2008 inspired further applications for wireless data transfer (label 7), and by 2009 the one billionth Wi-Fi chipset was sold, encouraging U.S. President Barack Obama to commit an additional 500 MHz of spectrum for the wireless industry in 2010 (label 8).

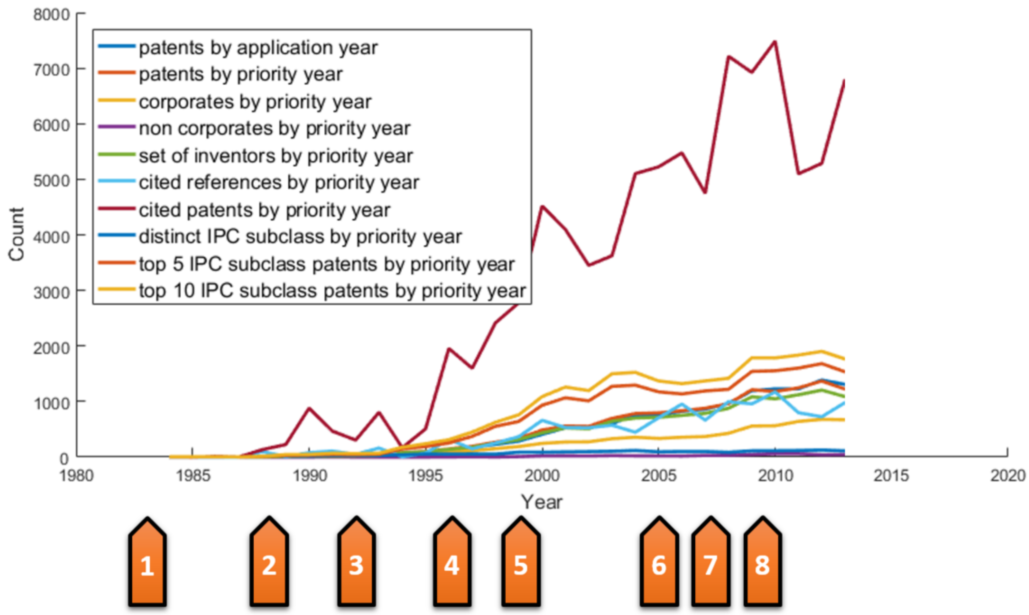


Figure 5.24: Development trends for wireless data transfer relative to historical events

5.5.24 Conclusions from extracted patent datasets

These patent data timelines illustrate how the development of emerging technology is dependent upon both technological and socio-economic factors. The relationship between development activities and political or economic backing recorded in historical narratives is observable at many of the key growth spurts for the technologies considered here. In this regard, the chronological profiles reflect the non-sequential nature of technology development observed by Gooday and Edgerton [Gooday, 1998, Edgerton, 2011]. This is important, as it provides evidence to suggest that the extracted bibliometric indicators do in fact capture many of the real-life socio-economic, political, and organisational events that have taken place, and that influence the growth of a new technology beyond purely technological developments. Consequently, when developing the technology diffusion model discussed in the next chapter, socio-economic effects are assumed to be already captured in the driving input data, so are not included as separate parameters to avoid double counting errors or biases.

It is worth noting here the fuzzy nature of combining semantic searches with classification boundaries, which means it is not always possible to retrieve every patent associated with a given technology. This is because patent search results depend on search terms matching the selection of keywords, nomenclature, and categories used by both the original inventors and subsequent pattern attorneys (which may be from a different era). This, inherently, does not happen in all cases due to the versatility and fluid nature of human languages. However, the extracted profiles demonstrate a good reflection of major events and influences recorded during the development of the selected technologies, and so are felt to be a suitable representation of the critical factors shaping technology adoption.

5.6 Technology Life Cycle stage matching process

With bibliometric profiles extracted for each of the technologies considered, the first stage of analysis identifies transition points between different Technology Life Cycle stages to establish time series segments for use in comparative analysis. For the technologies considered, evidence was identified from literature to suggest when these transitions had occurred, such as in the innovation timeline assessments prepared for a range of technologies by Hanna (see Fig. 5.25 to 5.27).

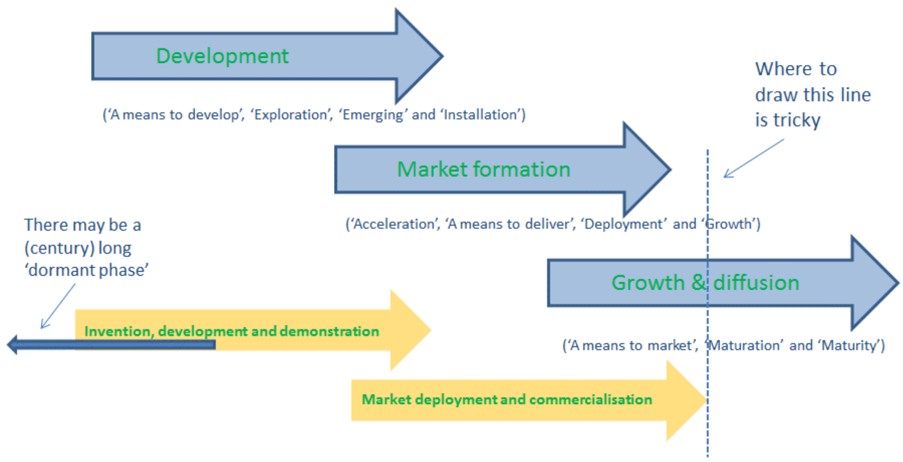


Figure 5.25: Phases of the innovation timeline [Hanna et al., 2015]

As noted in section 2.1, considerable ambiguity exists over the delineation of technology development efforts into clearly defined TLC stages [Gooday, 1998, Edgerton, 2011]. Locating an exact start or end point, and consequently, duration of each TLC stage (such as those in Figs. 5.26 and 5.27) is complicated by the non-sequential shifts observed in reality between different evolutionary states, and overlapping dependencies between components of complex products that evolve in parallel.

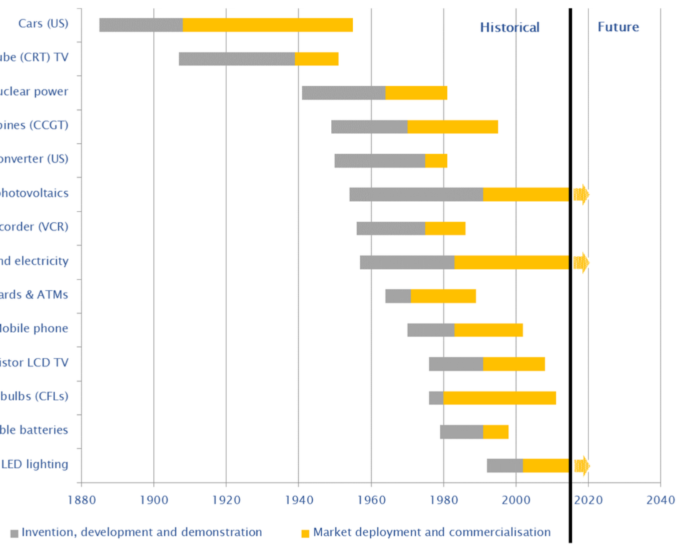


Figure 5.26: Historical timeline and duration of innovation for technologies reviewed by UKERC [Hanna et al., 2015]

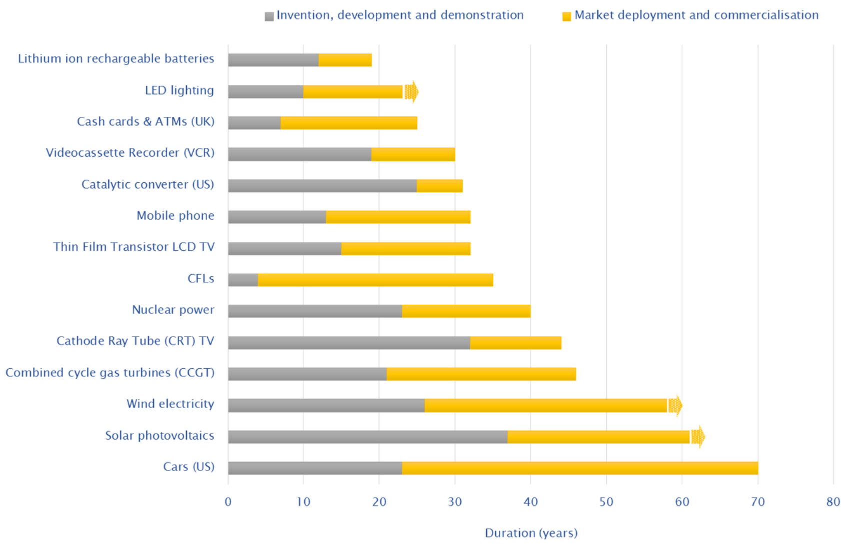


Figure 5.27: Duration of development and commercialisation of technologies reviewed by UKERC [Hanna et al., 2015]

In this regard, the current study adopts transition point definitions described in [Hanna et al., 2015] to enable comparative technology assessments. Hanna's work assumes dates of *invention*, *market introduction*, and *widespread commercialisation* for a technology act as boundaries for the *emergence* and *growth* stages of the TLC. In many cases, the invention and market introduction dates can be established without great confusion, although the point of widespread commercialisation (signalling the start of the *maturity* phase) is less obvious. Accordingly, Hanna provides three possible definitions for this point, dependent on the type of innovation considered. These are summarised in Table 5.3.

Whilst this does not resolve the ambiguity associated with complex narratives of technology development, applying these definitions uniformly at least allows reasonable comparisons to be made

Table 5.3: Definitions for the point of widespread commercialisation provided by Hanna [Hanna et al., 2015]

Innovation category	How widespread commercialisation is defined in this study	Geographies applicable
Novel products or technologies for new markets	When 20% of maximum cumulative units was reached[2]	UK, US, EU
Replacement products or technologies	When the market share of the replacement innovation overtook that of the incumbent / rival products and became the dominant market share (measured either by annual sales or cumulative units)	UK, US, Europe, OECD and global
Energy generation technologies	10% share of electricity production.	UK, global

between technologies being evaluated. Equally, other definitions could be used for transition points that would result in different conclusions from those presented in this analysis. However, as the analysis in this and the next chapter focuses solely on the emergence stage, the dates of invention and market introduction are the points of interest here. The definitions for the point of widespread commercialisation are quoted here purely for extension to other TLC stages in future studies. Using Hanna's definitions the transition points compiled for the current study are provided in Table 5.4 [Hanna et al., 2015]. These points define the time series segments each technology dataset was decomposed into relative to evidence presented by the complete historical development profiles and narratives.

Of the 23 technologies in Table 5.4, 20 had patent data pertaining to the emergence stage (i.e. excluding incandescent lights, landline telephones, and wireless data transfer). Therefore only those technologies with patent data available from the emergence stage are considered in the following analysis.

For subsequent expansion of this analysis to additional technologies where literature evidence is not immediately apparent for defining these segments, a *nearest neighbour* pattern matching process was also developed, as discussed in section 4.7.1 based on the work of Gao et al. [Gao et al., 2013]. This enables TLC segments to be defined from observed patent profiles. An overview of this process is shown in Fig. 5.28.

This process uses training technologies to classify the transitions between TLC stages for each test technology considered. Based on the evidence of Hanna and Gao [Hanna et al., 2015, Gao et al., 2013], eight training technology profiles were available for this classification exercise, as opposed to the two

Table 5.4: Technology Life Cycle transition points based on literature evidence

Case study	Section	Last year of Emergence stage	Last year of Growth stage	Last year of Maturity stage	Technology Life Cycle transition point sources
Compact Fluorescent Lamps	5.5.1	1979	2011	–	[Hanna et al., 2015, Weiss et al., 2008]
Electric vehicles	5.5.2	1997	2005	–	[Ranaei et al., 2014, Yuan and Miyazaki, 2014]
Fibre optics (data transfer)	5.5.3	1970	1990	–	[Cattani, 2006, Hecht, 2004]
Geothermal electricity	5.5.4	1958	–	–	[Glassley, 2014]
Halogen lights	5.5.5	1959	–	–	[Waide et al., 2006, Menanteau and Lefebvre, 2000, Navigant Consulting (Europe) et al., 2009]
Hydro electricity	5.5.6	1956	1975	–	[Connelly and Sekhar, 2012]
Impact/Dot-matrix printers	5.5.7	1970	1984	1991	[Mayadas et al., 1986, Tomash, 1990, Agrawal and Dwoskin, 2003a, Clymer and Asaba, 2008, Acee, 2001]
Incandescent lights	5.5.8	1882	1916	2008	[Chang and Baek, 2010, Gendre, 2003, Navigant Consulting (Europe) et al., 2009]
Ink jet printer	5.5.9	1988	1996	2003	[Clymer and Asaba, 2008]
Internet	5.5.10	1982	2000	–	[Lemstra, 2006, Zakon, 1997, von Stackelberg, 2011]
Landline telephones	5.5.11	1878	1945	2009	[Ortt and Schoormans, 2004, Teltscher et al., 2013]
Laser printer	5.5.12	1979	1993	–	[Grant et al., 2013, Tomash, 1990]
LED lights	5.5.13	2001	–	–	[Hanna et al., 2015]
Linear Fluorescent Tube lights	5.5.14	1937	1990	2012	[Waide et al., 2006, Tidd et al., 1997, Köhler, 2013]
Nuclear electricity	5.5.15	1963	1981	–	[Hanna et al., 2015]
Solar PV	5.5.16	1990	–	–	[Hanna et al., 2015]
Solar thermal electricity	5.5.17	1968	–	–	[EIA, 2008a, Grübler et al., 2012]
TFT-LCD	5.5.18	1990	2007	–	[Gao et al., 2013]
Thermal printers	5.5.19	1972	1985	2002	[McLoughlin and Keong, 2001, Gregory, 1996, Tomash, 1990, Gerber Scientific, 2007, Red Bus Cartridges, 2017]
Tide-wave-ocean electricity	5.5.20	1966	–	–	[Tester et al., 2012, Corsatea, 2014]
Turbojet	5.5.21	1939	1958	–	[Geels, 2006]
Wind electricity	5.5.22	1982	–	–	[Hanna et al., 2015]
Wireless data transfer	5.5.23	1982	2002	–	[Hanna et al., 2015]

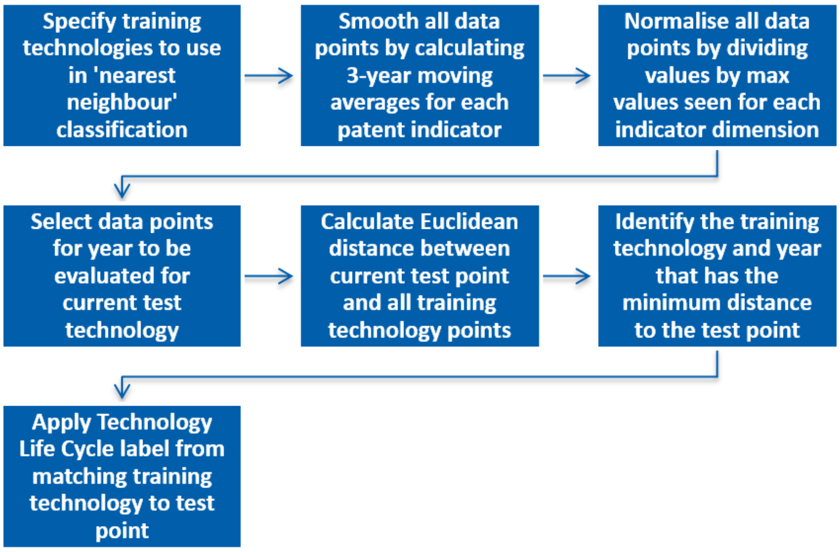


Figure 5.28: Overview of Technology Life Cycle stage matching process based on the work of Gao [Gao et al., 2013]

(TFT-LCD and CRTs) used in Gao's original work. Although different patent databases are used here, the basic patterns observed for the two training technologies in Gao's work are mostly captured in the records extracted using the Questel-Orbit tool. This is seen in Fig. 5.29, where extracted trends are compared against the original study.

Fig. 5.29 also shows some notable differences between the technology records extracted from the DII and the Questel-Orbit results. There are several reasons for this. Firstly, these databases do not hold exactly the same records. This was apparent from the record counts in [Gao et al., 2013], which reported several thousand fewer records for the exact same search query structures and filtration steps. This typically results from differences between the databases' coverage (regarding countries and time periods), and/or the searchable detail of available records. For example, whilst the DII covers 40 patent offices globally, with full text available for the majority of patents stored rather than just abstracts, it is limited to 2008 onwards. Secondly, since Gao's study in 2013, records for the later years will have been added due to the time lag between a patent being registered and archived on the database. There may also be discrepancies between database accounting methodologies for patent families, and the functionality of search algorithms used to identify records.

Considering the quality of extracted trends in more detail, many of the peaks in the Questel-Orbit data correspond to equivalent peaks in the DII data. However, not all align perfectly. There is also an observable difference in the *number of cited patents per year* trends, which seems considerably higher for the Questel-Orbit data. This may have signified a problem in the MATLAB script used here to extract patent indicators, potentially generating artificially inflated trends from double counting or similar systematic errors. To verify the script's performance, a separate examination of patent citation counts was conducted using Excel pivot tables for several batches of patent records (approximately 30,000 records), which found that the number of citations extracted using the MATLAB script matched very well those found using the Excel-based procedure. This analysis confirmed that the MATLAB

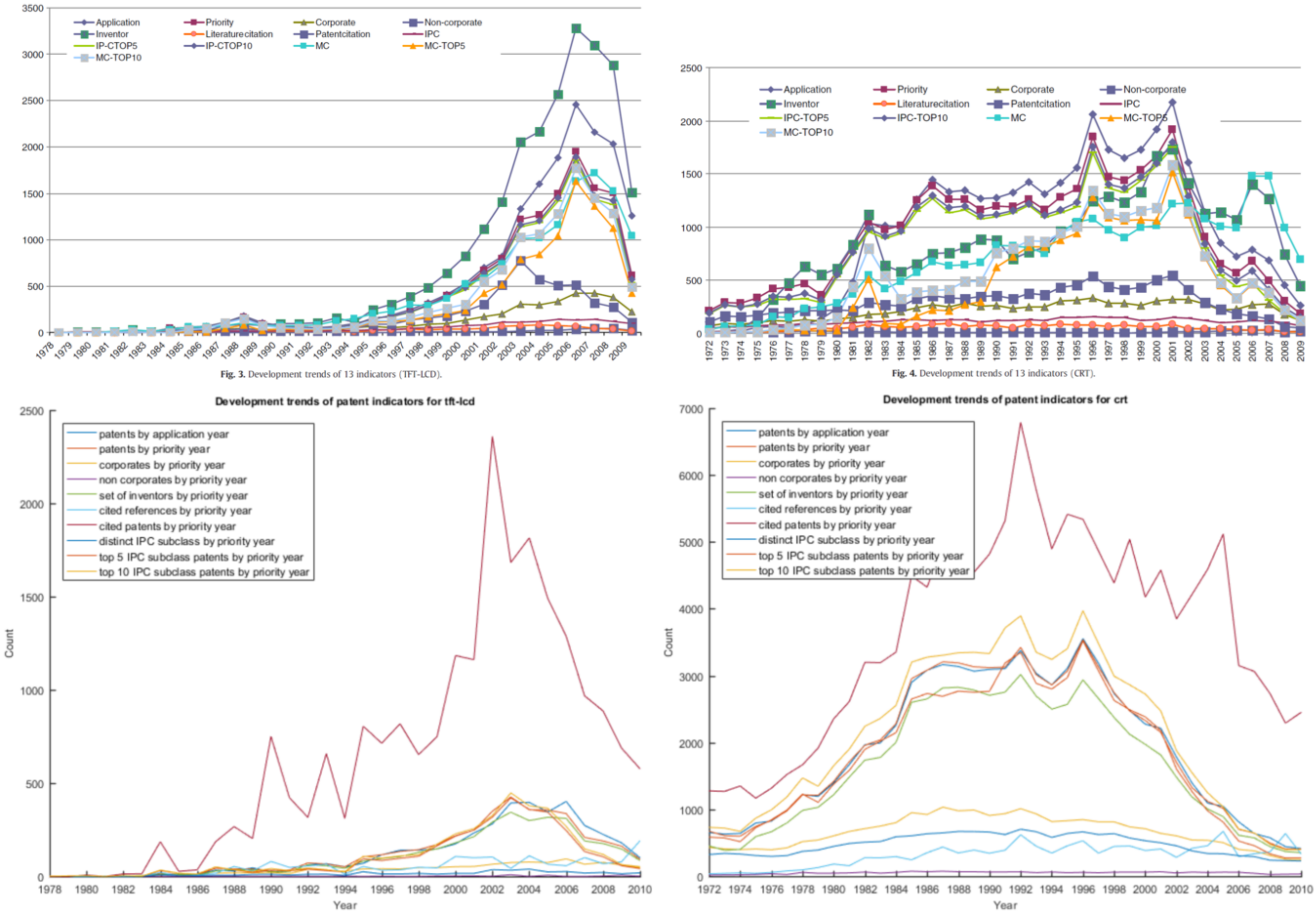


Figure 5.29: Comparison of extracted TFT-LCD and CRT training datasets based on the work of Gao [Gao et al., 2013]

data extraction script performed as expected, suggesting that observed discrepancies between Questel-Orbit results and DII records arose either as a result of recording differences when addressing citations in these databases, or as a previous analytical error. However, it is not felt that this discrepancy would significantly impact results in this study, as the nearest-neighbour matching process is based on amplitude normalised trends rather than absolute values, and therefore there is notably less variation in the trend values used (see Figs. 5.30 and 5.31). Normalisation in this manner prevents the *cited patents* indicator from unfairly dominating other trends in subsequent analysis.

With these discrepancies noted, the current training technologies correspond to timescales shown for CRTs, nuclear power, solar photovoltaics, wind electricity, mobile phones, TFT-LCD, and CFLs in Fig. 5.26. Having specified the training technology profiles, the MATLAB script (provided in Appendix D) smooths both training and test time series based on a three-year moving average, and normalises the amplitude, as per Gao's study (see Figs. 5.30 and 5.31).

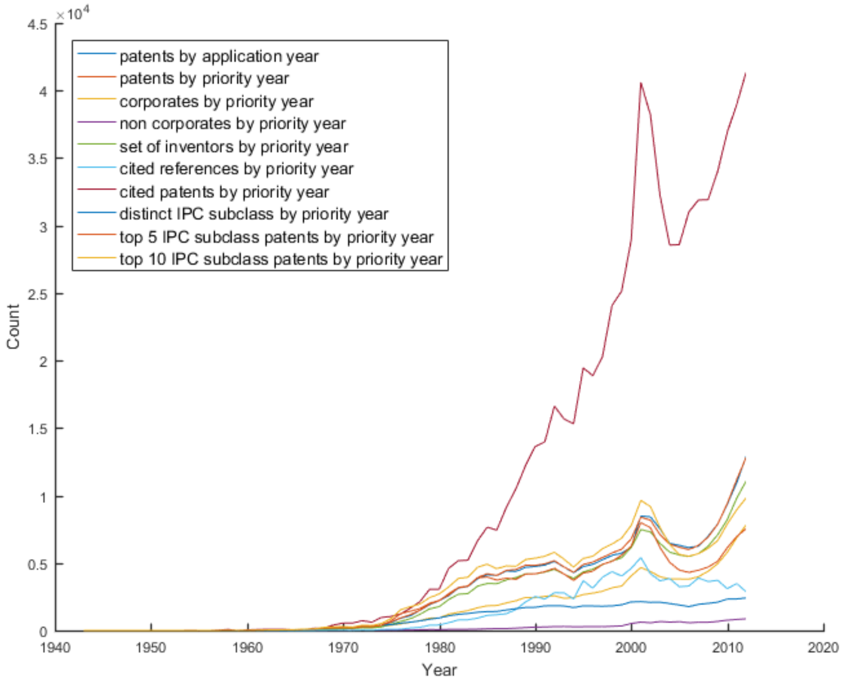


Figure 5.30: Original bibliometric trends for fibre optics extracted from Questel-Orbit data

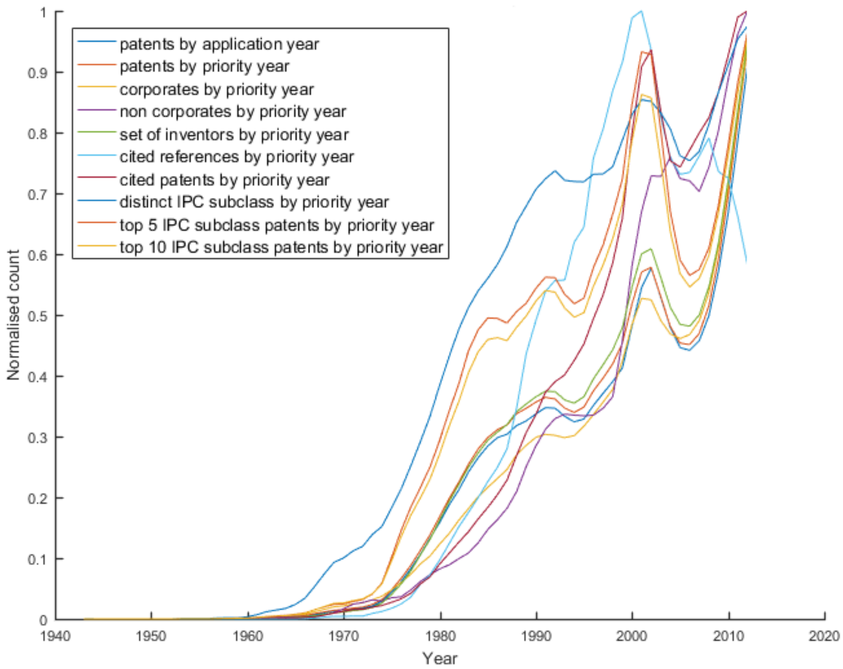


Figure 5.31: Smoothed and normalised bibliometric trends for fibre optics

Once the training and test datasets have been smoothed and normalised, the MATLAB script cycles through each year of the test technology records and calculates the Euclidean distance between the current test data point and all possible training technology data points. This process was illustrated by Gao (Fig. 5.32).

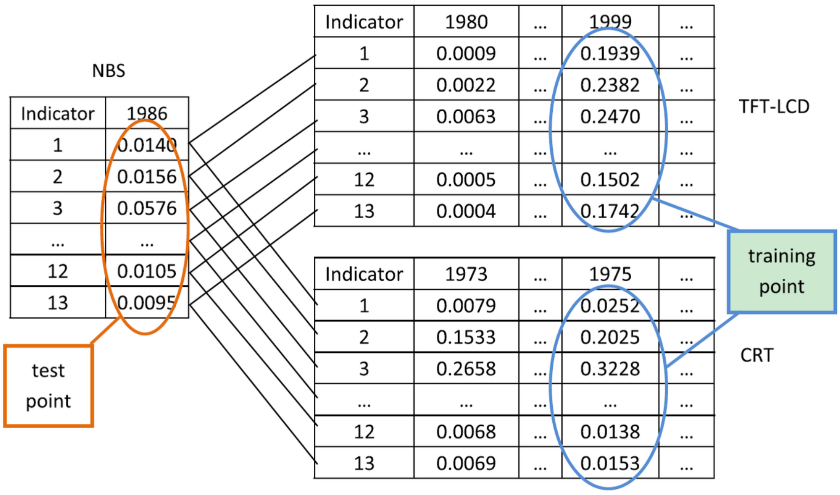


Figure 5.32: An example of computing the distance between test and training points [Gao et al., 2013]

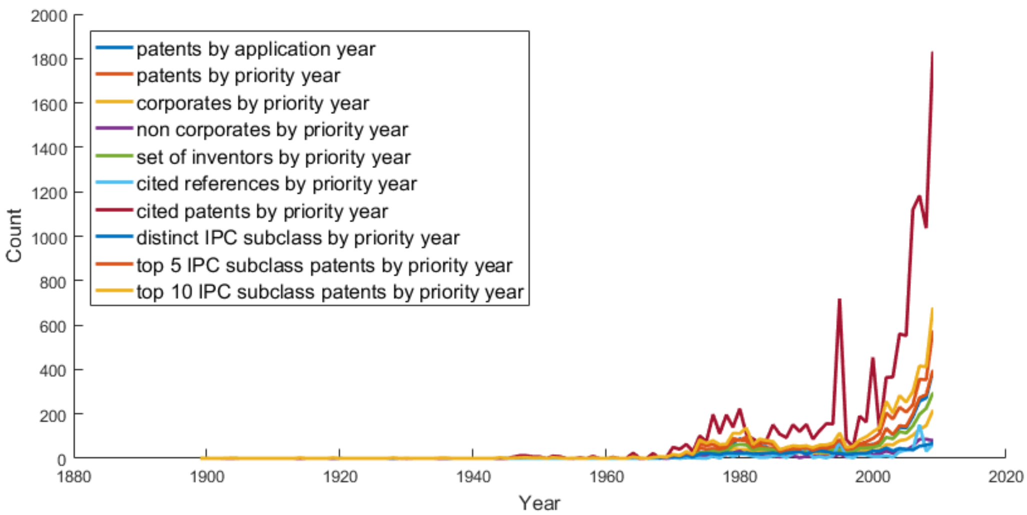


Figure 5.33: Geothermal electricity generation development trends

The closest training point is identified from the possible training technologies and years considered, with the test data point adopting the TLC stage label of the matching training point. The results of this nearest neighbour classification system are illustrated in Figs. 5.33 to 5.36 for geothermal electricity generation and impact/dot matrix printers, where it can be seen that development efforts generally correspond well to TLC stage transitions. Observed growth, plateau, and decline phases in the extracted technology profiles are broadly mirrored in the TLC stage profile. In these examples, a transfer function (or other suitable method) could then be used to convert the matched TLC profile into a real-time measure of life cycle progression. This would enable transition points between consecutive

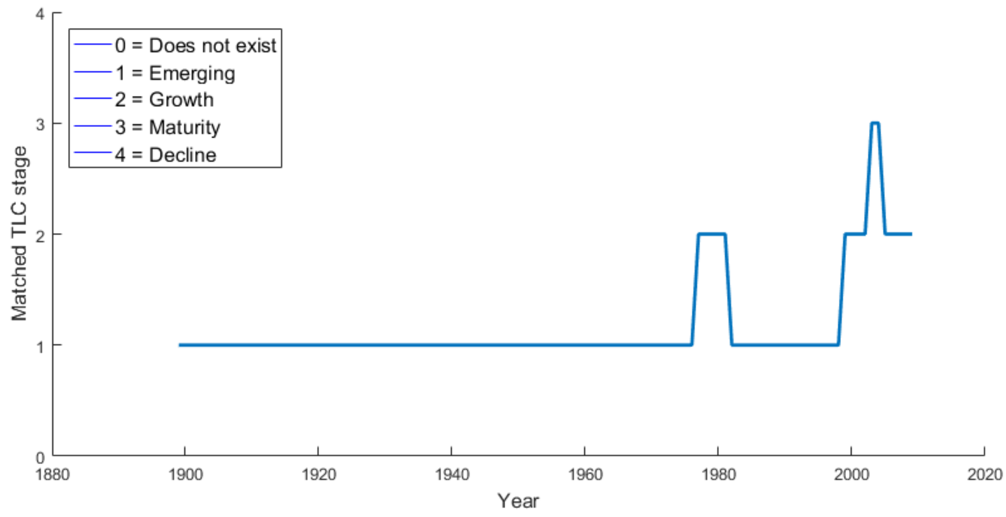


Figure 5.34: Matched TLC stages for geothermal electricity generation

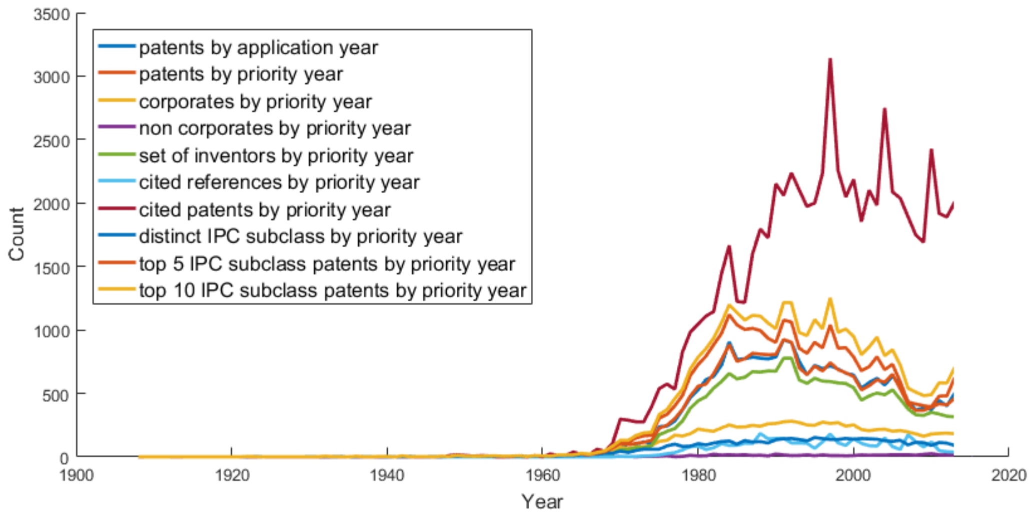


Figure 5.35: Impact/dot matrix printer development trends

stages to be estimated, and subsequently allow time series segments to be defined for technologies where literature evidence was not readily, or easily, available. It is worth remembering here that the TLC focuses on the maturity of technologies and development efforts to bring them to market, whilst technology diffusion and adoption deals with consumer behaviours after commercialisation. As such, progression through the TLC cannot automatically be associated with marketplace adoption levels without more information on market behaviours and the likely mode of adoption (discussed in the next chapter). Consequently, the matched TLC stage examples shown in Figs. 5.34 and 5.36 could be used to segregate time series into appropriate stages for subsequent analysis, but would not provide direct insight into adoption trends for these technologies without an accompanying market model. Equally, this nearest-neighbour approach provides varying results depending on the number of training technologies used in the matching process, distribution of the training technology profile types, and degree of smoothing applied. This procedure is primarily described to illustrate how the existing

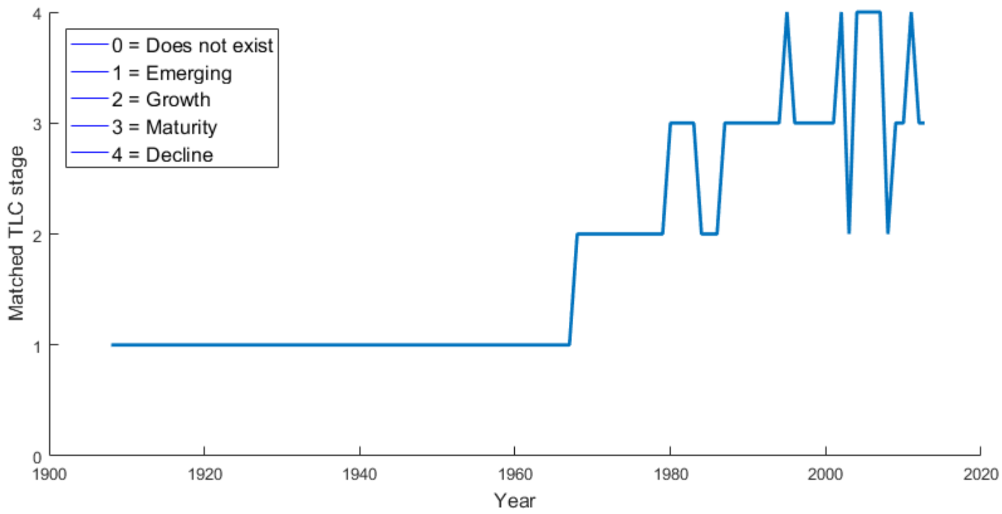


Figure 5.36: Matched TLC stages for impact/dot matrix printers

methodology can be extended to a wider range of technologies in the future. In light of this and the use of literature evidence for the technologies considered, an optimal training set is not identified as part of this work. Further experimentation and verification is therefore recommended if looking to apply this process on a larger scale.

5.7 Identification of significant patent indicator groups

Having defined time periods corresponding to each TLC stage for the technologies considered, it is now possible to segment the bibliometric time series into comparable phases of development. Significant predictors of substitution modes in each TLC stage are then identified by analysing data from each TLC stage separately, using the procedure outlined in Fig. 5.37.

As discussed in sections 4.7.2 and 4.7.3, an unsupervised learning approach has been employed based on applying Dynamic Time Warping and the 'PAM' variant of K-Medoids clustering on the relative distance measures calculated between time series. This is implemented as a MATLAB script (provided in Appendix D) based on MathsWorks' DTW and K-Medoid functions [MathWorks, 2016b, Stackoverflow.com, 2015a]. The first step of this process involves generating a list of all unique subsets that can be created from the 10 patent indicator metrics considered. This produces 1,023 (i.e. $2^{10} - 1$) possible combinations of patent indicators to be tested, as illustrated by Fig. 5.38.

Next, the raw patent data time series are transformed using an inverse hyperbolic sine function and normalised, to convert the data into a suitable format for long-term comparisons (see discussion on preprocessing in chapter 4). The data points are then filtered based on the current TLC stage being considered, as illustrated by Fig. 5.39, ensuring focus on comparable curve features.

After transforming the datasets and filtering based on the current TLC stage, DTW is used to calculate the Euclidean distance between each pair of technology time series when compared using the time series dimensions specified by each patent indicator grouping in turn. This process is depicted visually

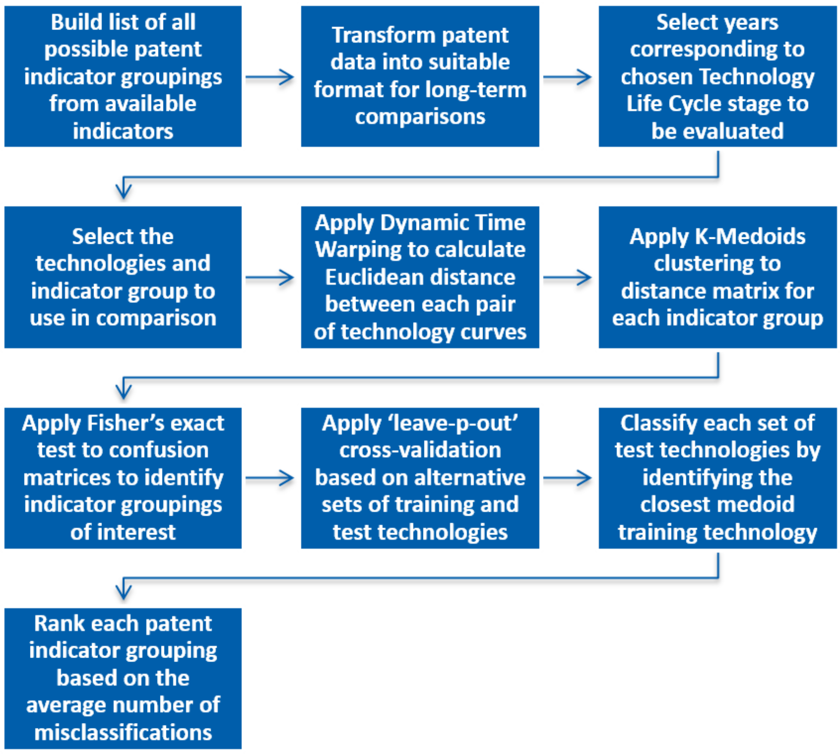


Figure 5.37: Overview of the process used to identify and rank significant patent indicator groups

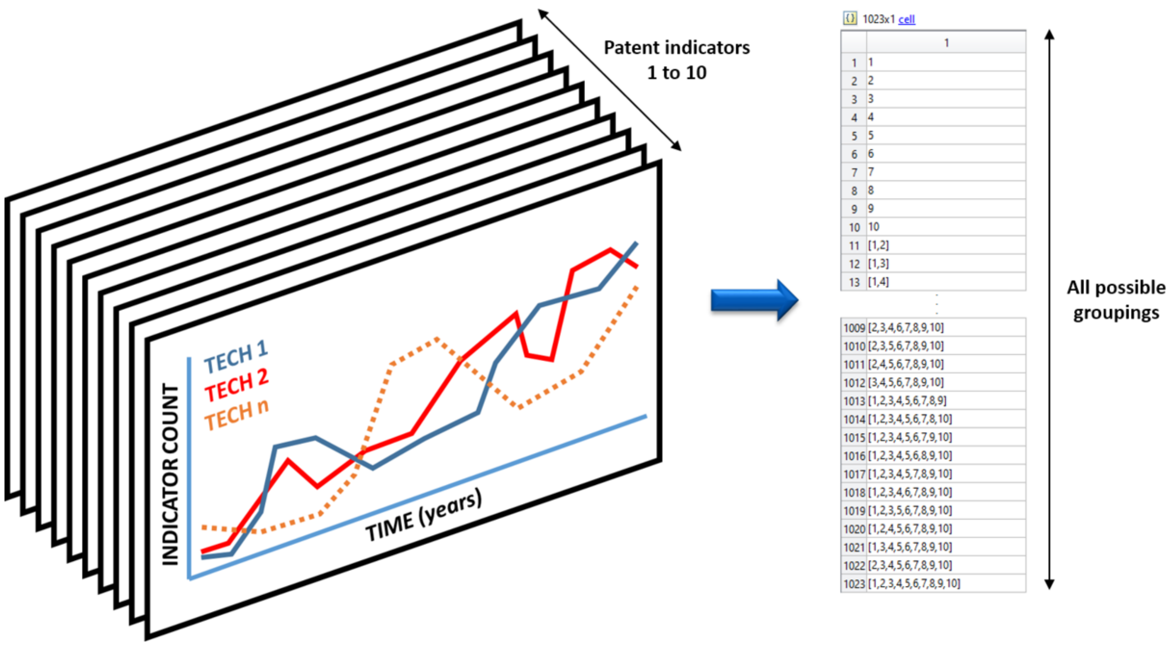


Figure 5.38: Generating list of all possible patent indicator groupings from time series dimensions considered (for illustration purposes only)

in Fig. 5.40, illustrating the successive layers of filtering that are applied for each technology pairing and each patent indicator grouping considered. Fig. 5.40 also provides an illustration of how the DTW alignment process distorts technology profiles to reduce the dissimilarity between the multidimensional

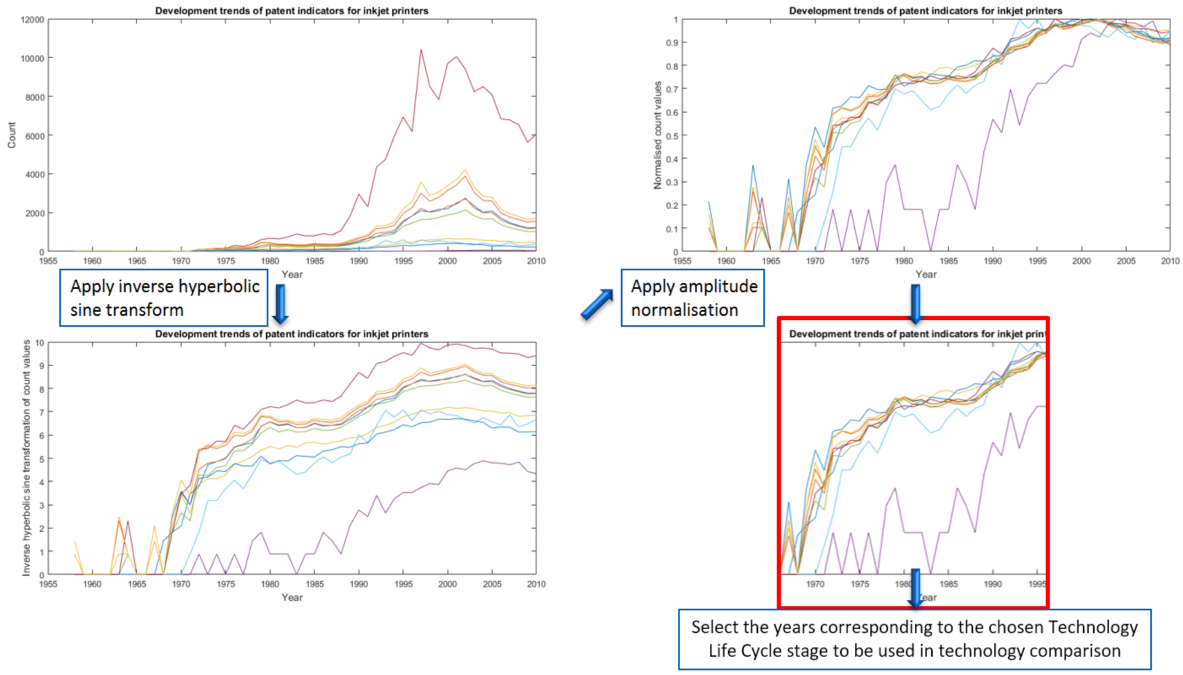


Figure 5.39: Transforming extracted patent data time series into a suitable format for long-term comparisons (for illustration purposes only)

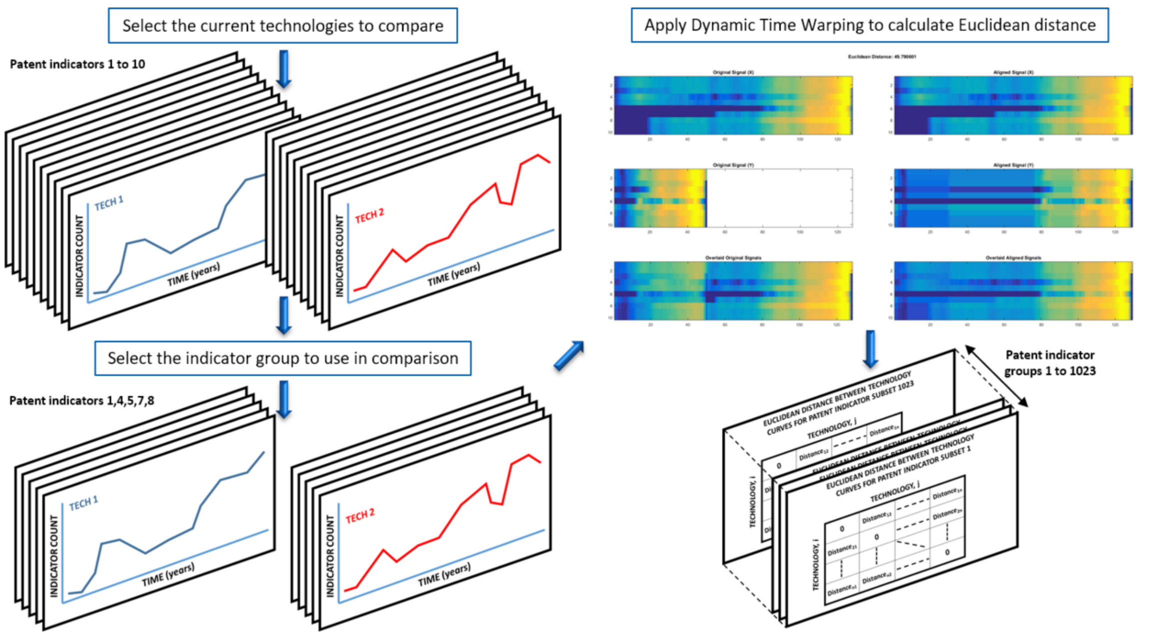


Figure 5.40: Calculating the distance between each pair of technology time series for each indicator grouping (for illustration purposes only)

sets of features being compared (i.e. in this case aligning two ten-dimensional signals spanning different time periods). The output from this process is an *i* x *j* x 1023 distance matrix, where *i* and *j* specify the current technology pair, and the value quoted is the measured distance between multi-dimensional time series based on the current patent indicator subset. In parallel, the corresponding warping paths required

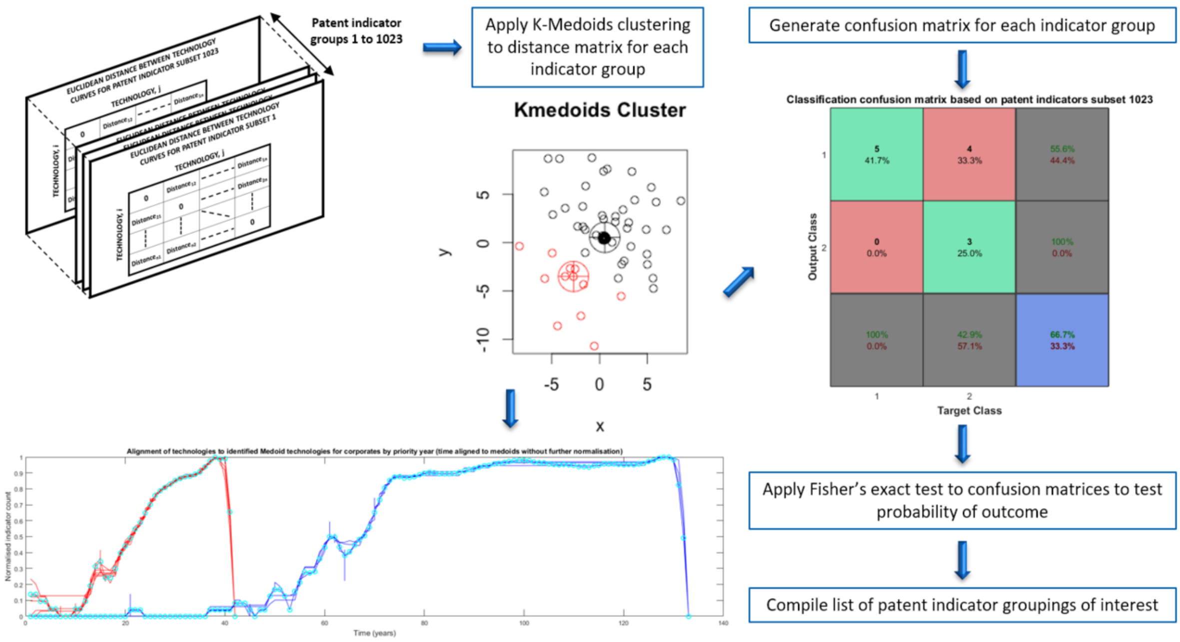


Figure 5.41: Identifying patent indicator groups of interest (for illustration purposes only)

to measure the distance between the N-dimensional curves in each condition are stored in two separate matrices for later use.

Using this distance matrix it is now possible to apply K-Medoids clustering to determine the technology groupings predicted when each patent indicator subset is used. By comparing the predicted technology groupings to those expected from the earlier literature classifications (see section 2.5 and Table 5.2), a confusion matrix is created for each patent indicator subset that shows the alignment between predicted and target groupings (illustrated in Fig. 5.41). Fisher's exact test is then applied to each confusion matrix to calculate the probability of obtaining the observed clusters. In doing so, significant patent indicator subsets are identified based on those that have less than a 5% chance of natural occurrence.

5.8 Ranking of grouped patent indicator dimensions

As discussed in sections 4.3.1, 4.3.5, and 4.7.3 *leave-p-out* cross-validation techniques provide a means to rank bibliometric indicator subsets that have been identified as producing a significant match to the expected technology groupings. More specifically, this form of permutation testing provides an estimate of how accurately the current predictive model will perform in out-of-sample conditions (based on the results produced from using numerous reduced forms of the in-sample data sets). The first stage of this process consists of generating lists of all possible training technology and corresponding test technology combinations, when leaving one technology out at a time. Leave-one-out cross-validation was selected to ensure that a sufficient number of resampling points were present in each K-Medoids training set. This enables meaningful clusters to be formed whilst still allowing a sufficient number of permutations to be tested. The procedure then progresses in a similar format to the initial calculation of distances between each pair of technology time series (shown in Fig. 5.40), except that this time distance measures are only calculated between pairs of training technologies, and the process is repeated for every possible combination of available training technologies. As such, the output from this process is now an i x j x 1023 x n distance matrix, where i and j now specify the current **training** technology pair considered, and n represents the number of training combinations that can be used. This is illustrated in Figs. 5.42 and 5.43.

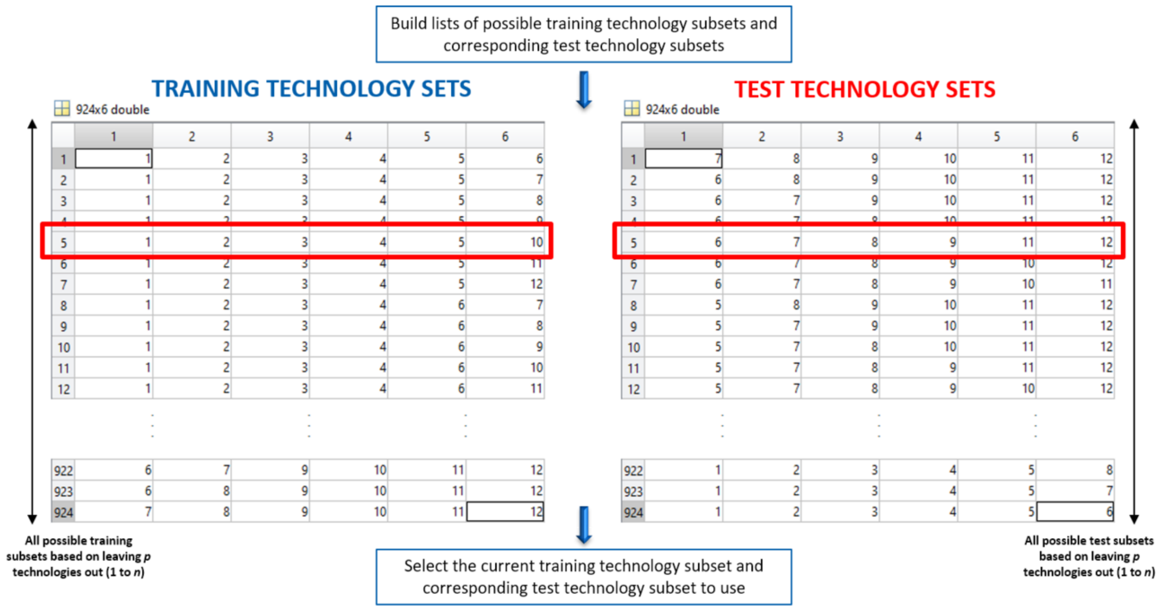


Figure 5.42: Building lists of possible training technology subsets and corresponding test technology subsets (for illustration purposes only)

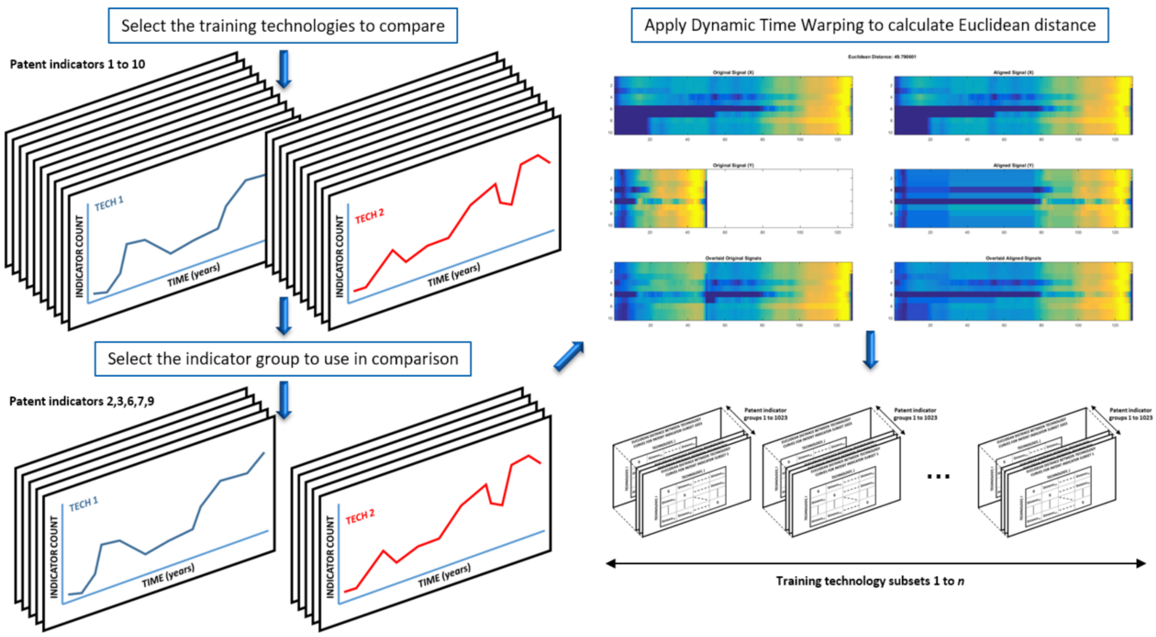


Figure 5.43: Calculating the distance between each pair of training technologies for each indicator grouping (for illustration purposes only)

K-Medoids clustering is once again applied to the resulting training technology distance matrices, from which two medoid technologies are identified for each patent indicator subset, in each training condition. The test technologies can now be evaluated individually against the two medoid curves identified in each training condition, to determine the closest medoid to the current test technology. This provides a classification for the test technologies based on each training condition and each patent indicator subset. Comparing predicted and expected technology classifications provides a count of the number of misclassified test technologies for the current combination of training technologies and patent indicators. This in turn is used to calculate the average number of test technologies misclassified for each patent indicator grouping across all of the training conditions considered. In this instance this means that each of the 1,023 possible patent indicator subsets is assessed for predictive performance, based on data only pertaining to the emergence stage, against 20 different training technology combinations. Consequently, an average misclassification value of *1* indicates that test technologies were incorrectly classified in all test conditions for the current patent indicator subset, whilst a value of *0* indicates no misclassifications in any test conditions. Using the average number of misclassifications ensures a symmetrical and unbiased treatment of all patent indicator groupings considered. Finally, the results are sorted by the minimum average number of misclassifications, to rank the robustness of each patent indicator grouping. This procedure is illustrated in Fig. 5.44.

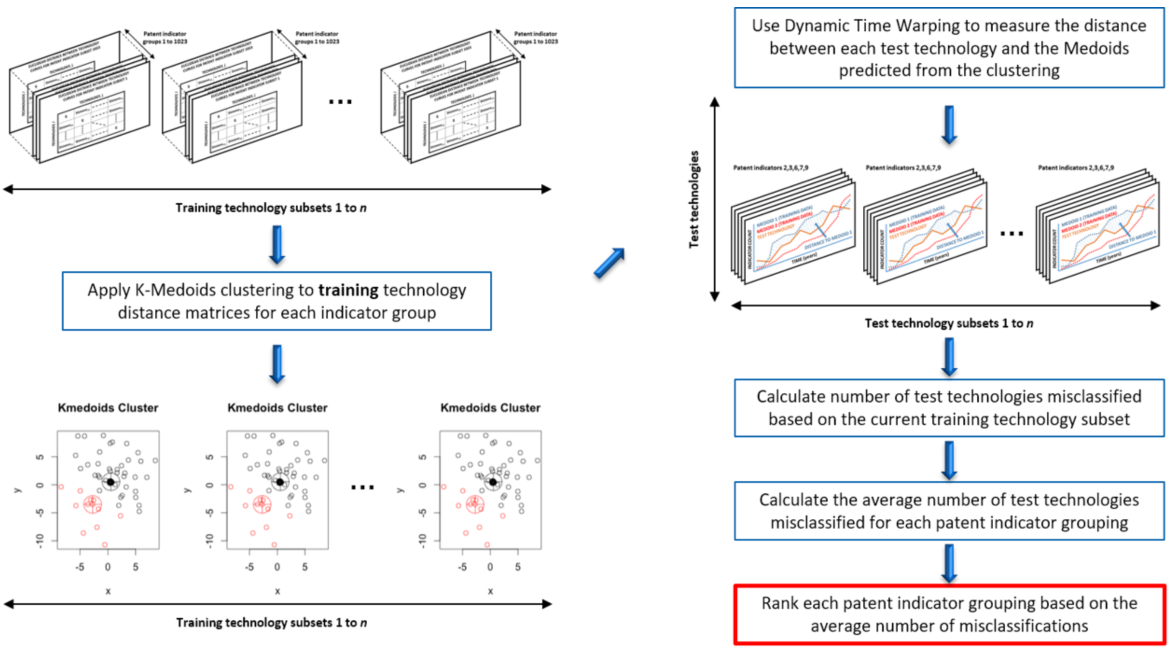


Figure 5.44: Ranking of grouped patent indicator dimensions (for illustration purposes only)

From this ranked list of patent indicator subsets, the frequency of occurrence of individual patent indicators in the top ranked subsets can be observed. This is shown in Table 5.5 for the top performing 15% of subsets, with the average number of misclassifications against each subset. From this, the combination of indicators 4 and 6 is observed to appear in all of the best performing subsets (i.e. the four subsets that average a misclassification value of 0.1), whilst reappearing consistently in the majority of the remaining indicator subsets that achieve average misclassifications of less than 15%.

This does not mean that all combinations with indicators 4 and 6 should automatically be used, as some sets containing additional indicators may have counter-acting effects. This is apparent in this analysis, since all combinations with indicators 4 and 6 have been calculated, with only those in Table 5.5 achieving the best levels of performance. It is normally advisable in model building to use as few parameters as possible (i.e. a parsimonious model), so Table 5.5 suggests that indicators 4 and 6 would be most appropriate for the classification scheme considered.

Table 5.5: Frequency of patent indicators in the top ranked subsets

Average number of misclassified test technologies	Subset	Subset indicators									
		1	2	3	4	5	6	7	8	9	10
0.1	[1,4,6]	X			X		X				
	[2,4,6]		X		X		X				
	[4,5,6]				X	X	X				
	[1,4,5,6]	X			X	X	X				
Frequency [<10% misclassified]		2	1	0	4	2	4	0	0	0	0
0.15	[2,4]		X		X						
	[4,5]				X	X					
	[4,6]				X		X				
	[4,7]				X			X			
	[1,2,4,6]	X	X		X		X				
	[2,4,5,6]		X		X	X	X				
	[1,2,3,4,6]	X	X	X	X		X				
	[1,2,4,5,6]	X	X		X	X	X				
	[2,4,5,6,7]		X		X	X	X	X			
	[2,4,6,7,9]		X		X		X	X		X	
	[2,4,6,7,10]		X		X		X	X			X
	[2,4,6,8,9]		X		X		X		X	X	
	[2,4,6,8,10]		X		X		X		X		X
	[1,2,3,4,5,6]	X	X	X	X	X	X				
	[2,3,4,6,8,9]		X	X	X		X		X	X	
	[2,3,4,6,8,10]		X	X	X		X		X		X
	[2,4,6,8,9,10]		X		X		X		X	X	X
	[2,3,4,6,8,9,10]		X	X	X		X		X	X	X
Frequency [<15% misclassified]		6	16	5	22	7	19	4	6	5	5

5.9 Functional model building process

The ranking of different bibliometric indicator subsets provides a means to identify time series dimensions that, when combined, are most likely to provide robust out-of-sample predictions of observed technological substitution modes. These indicators are therefore expected to form a reasonable basis for Adner's classification scheme. However, for subsequent causal exploration (discussed in the next chapter), it is also necessary to trace the evolution of both observed technology profiles and corresponding mode predictions over time. For this, continuous time series are required. As such, a time-based regression model of mode prediction is also desirable, enabling technological development and substitution dynamics to be mapped directly against historical events, whilst accounting for the phase variation observed between different technologies. In this manner, variation in the patent measures defined in Table 5.1 is considered separately from phase variation between technologies, enabling model variance to be more accurately mapped to specific influences [Goldstein, 2011, Gelman and Hill, 2006]. This ensures that standard errors, confidence intervals, and significance tests are not misled by incorrectly aggregating distinct influences (i.e. overlaying influences specific to individual patent metrics with those linked to phase variance effects) [Goldstein, 2011]. Equally, the use of clustering means that this approach is less error prone and sensitive to outliers than using classical regression techniques in isolation [Joshi, 2017]. Conversely, clustering provides limited insight into the residuals and variance associated with predictions of individual technologies, whereas the methods now applied enable further exploration of uncertainty in these predictions. Lastly, while the approach described in this section can generate a technology classification model without the preceding cross-validation and ranking exercises, doing so would not provide insight into how the chosen patent indicator subset may perform in comparison to other subsets, in terms of out-of-sample predictive capabilities. This means that in-sample classification results could potentially match those produced by other model variants, but when extended to new test cases the performance could vary drastically. The goodness-of-fit measures and permutation testing discussed in sections 5.9.5, 5.9.6, and 5.9.7 subsequently verify that the model developed here conforms to predictive expectations inferred from the cross-validation exercises. The preceding cross-validation exercise therefore provides a basis for an informed selection of time series components to use in model building. Drawing on these findings, a time-dependent technology classification model is now developed using functional data analysis (see sections 4.3.6 and 4.7.4), based on the best performing indicators (i.e. the *number of non-corporate assignees* and the *number of cited references by priority year*).

Besides being present in all of the highest scoring sets of top ranked predictors, the chosen patent dimensions can potentially be associated with the rate of development in technology and science. This is in the sense that *cited references* show a clear link to scientific production that directly influences technological development efforts, whilst the *number of non-corporates by priority year* (i.e. universities, academies, non-profit labs and technology research centres) is associated with the amount of laboratory work required to commercialise a technology. More specifically, a large volume of lab work could indicate a lack of technological maturity, or considerable complexity in the emerging technology. By contrast, technologies with reduced non-corporate activity may be simpler and mature more rapidly or intuitively. *Non-corporates by priority year* could therefore equate to a measure of technological complexity, or effort required to mature.

It is also worth noting that there are other patent indicator subset couples/triples that perform nearly as well. It is possible that these other high-performing subsets may be in some way related to the chosen indicators. Perfect orthogonality cannot be assumed between these metrics, and in reality is highly unlikely, as suggested by the correlation analysis in Gao et al. [2013]. Consequently, it was decided to use the indicators specified as these appear to be the most statistically robust, whilst also in good agreement with previous literature conclusions (discussed in [Kuhn, 1996, Constant, 1973] and chapter 2).

Following the introduction to functional data analysis in section 4.3.6, and detailed methods in [Ramsay et al., 2009], the method outlined in Fig. 5.45 has been implemented in MATLAB for building a functional linear regression model for technology classification (the script is available in Appendix D for further details).

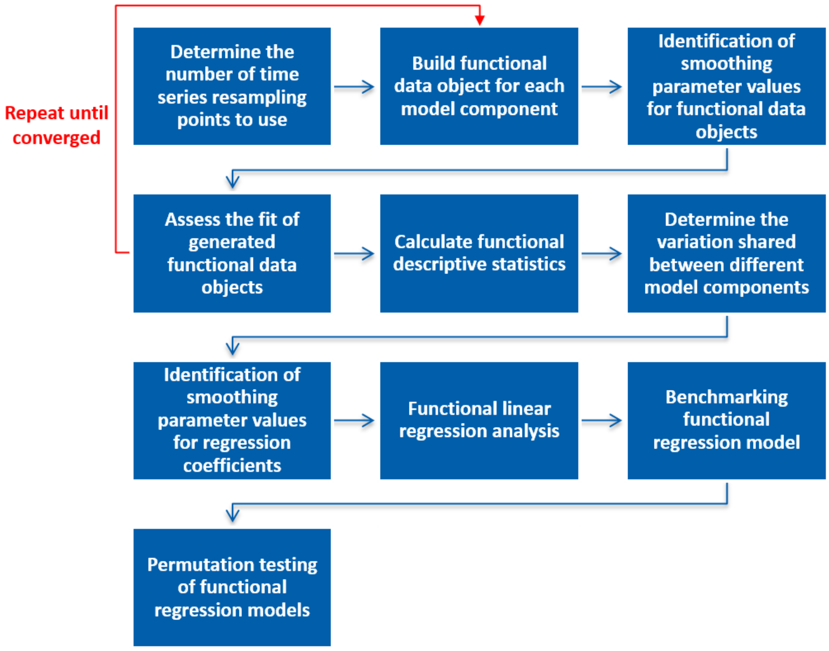


Figure 5.45: Functional model building process based on methods outlined in [Ramsay et al., 2009]

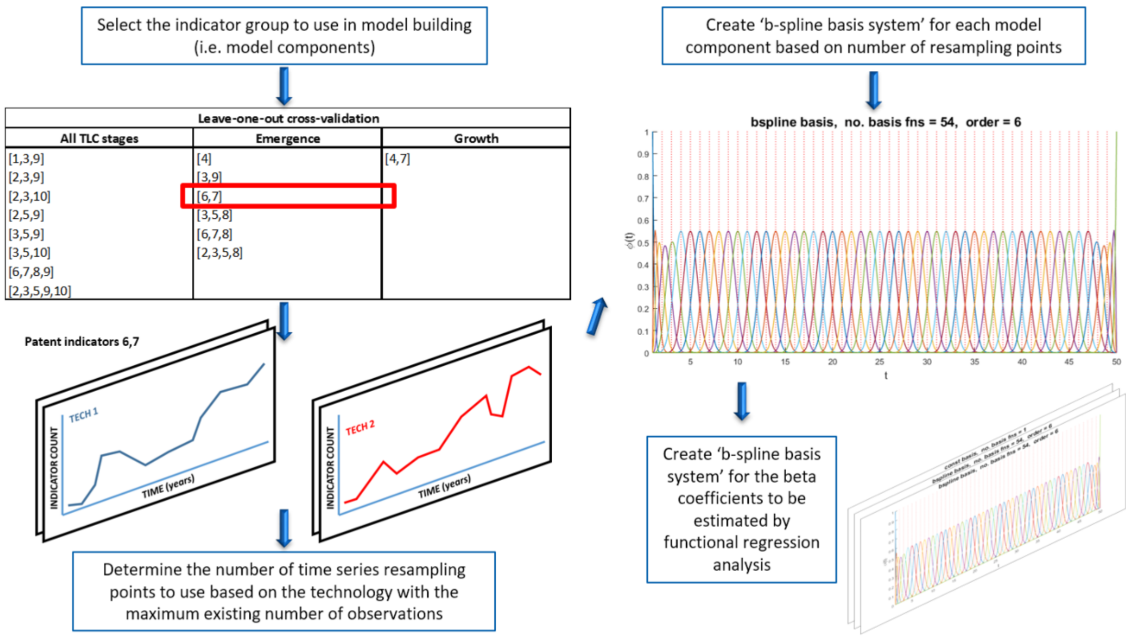


Figure 5.46: Building functional models of selected patent indicator groupings (for illustration purposes only)

Taking the chosen time series dimensions as a starting point, a *functional data object* must first be created for each of the patent indicators (or *model components*) included in the chosen subset. This is necessary to combine all of the technology profiles considered into two regression terms: one representing the *number of non-corporates by priority year*, and a second representing the *number of cited references by priority year*. These terms, when multiplied by their regression coefficients (calculated in the subsequent regression analysis), provide the relationship between the predicted mode of substitution and the two selected measures of science and technology. However, as the TLC segments being combined have a different number of observations for each case study technology, it is necessary to resample the segmented time series based on a common number of resampling points. This ensures that even if a TLC stage spans 20 years in one time series, and 50 years in another, both time series will have 50 observations. This enables the two curves to be aligned relative to each other for the current TLC stage. Next, a B-spline basis system is created for each model component based on the common number of resampling points defined, and also for the regression coefficients (β_i) to be estimated by the functional linear regression analysis (see Eqs. 4.1 and 4.3, and sections 3.4.1, 3.4.2, 9.4.1 and 9.4.2 of [Ramsay et al., 2009]). Fig. 5.46 provides an illustrative example of how three B-spline basis systems are combined, corresponding to a single constant regression term in addition to two terms relating to the selected model components.

5.9.1 Identification of smoothing parameter values for functional data objects

Before functional data objects can be generated from the B-spline basis systems, the degree of curve smoothing to be applied has to be determined (i.e. the tightness of fit). Following the process in [Ramsay et al., 2009] a *functional parameter object* that allows smoothness to be imposed on estimated functional parameters is created (see section 5.2.4 of [Ramsay et al., 2009]). Functional parameter objects extend the existing datasets, by storing additional attributes relating to the smoothness constraints that need to be respected in any B-spline curve fit. A functional data object is then created for the current model component, using the new functional parameter object and an initial value of the smoothing parameter (λ). The degrees of freedom and generalised cross-validation criterion coefficient (see section 5.3 of [Ramsay et al., 2009]) can then be calculated for the current functional data object. By repeating this process for a range of λ values and plotting the results (see Figs. 5.47 to 5.50) a suitable smoothing parameter can be identified to use in the final functional data object for each model component.

Selection of a smoothing parameter in this fashion ensures that the functional data object will have the best chance of capturing dynamics present in the data, whilst being more likely to fit future out-of-sample technologies. The resulting smoothed functional data objects for the number of non-corporate assignees and cited references in each priority year, for the technologies considered, are illustrated in Figs. 5.51 and 5.52, and Figs. 5.53 and 5.54 respectively. These examples illustrate how technology development profiles are realigned to an equivalent time span, the duration of which is based on using either a) each technology's complete historical profile, or b) specific comparable TLC stages, in the analysis. In these examples, the generated functional data objects have been restricted to covering only the *emergence* phase. It is worth noting that although multiple technology profiles are shown in Figs. 5.52 and 5.54,

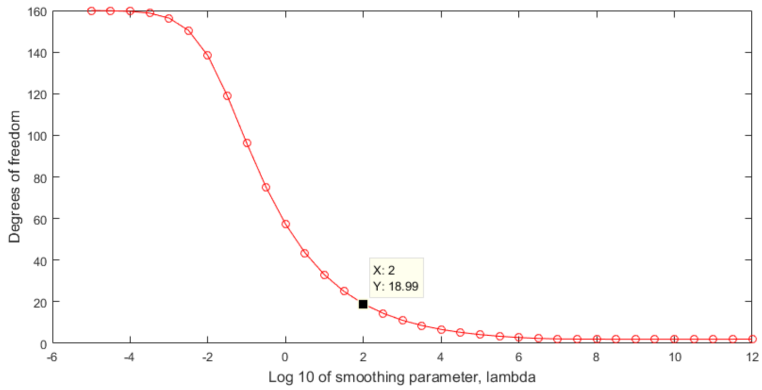


Figure 5.47: Degrees of freedom for functional parameter object smoothing parameters to fit *non-corporates by priority year* (based on emergence stage)

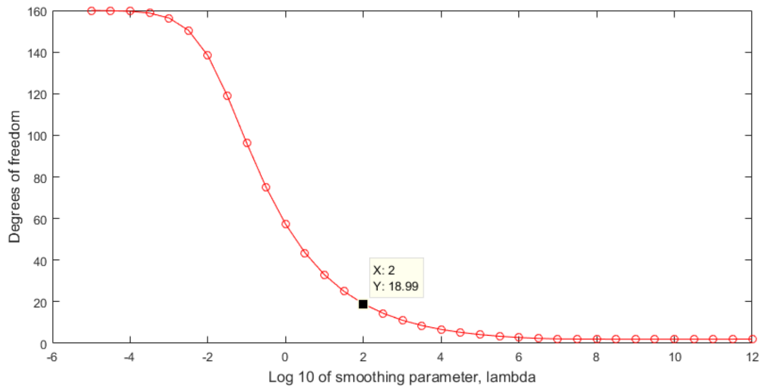


Figure 5.48: Degrees of freedom for functional parameter object smoothing parameters to fit *cited references by priority year* (based on emergence stage)

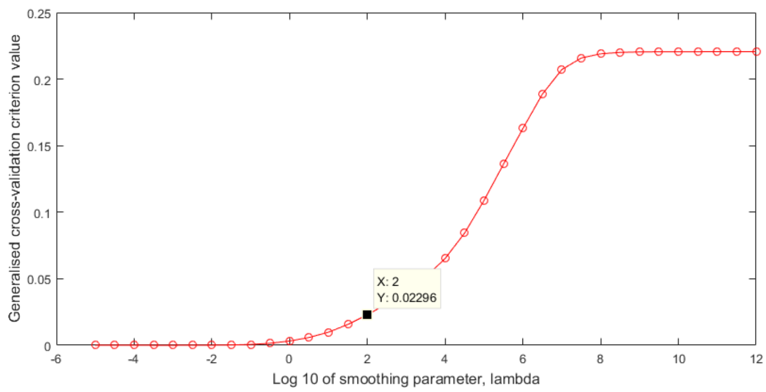


Figure 5.49: Generalised cross-validation scores for *non-corporates by priority year* functional parameter object smoothing values (based on emergence stage)

as a functional data object, these curves are treated as a single data object when applied in the later functional regression analysis. In this regard, a single model component (i.e. each patent indicator) includes curves representative of all technologies considered.

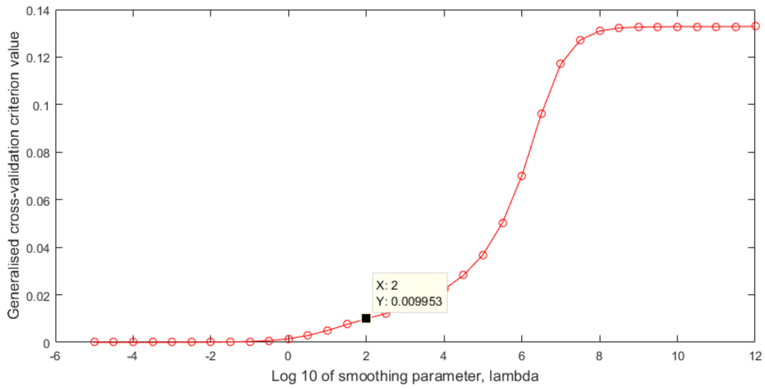


Figure 5.50: Generalised cross-validation scores for *cited references by priority year* functional parameter object smoothing parameter (based on emergence stage)

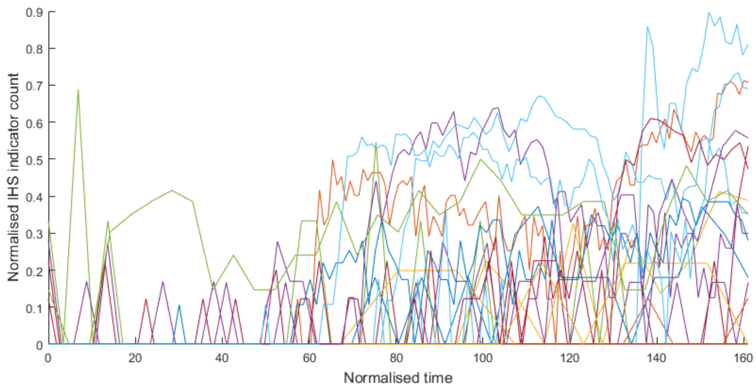


Figure 5.51: Technology profiles for *non-corporates by priority year* during the emergence stage

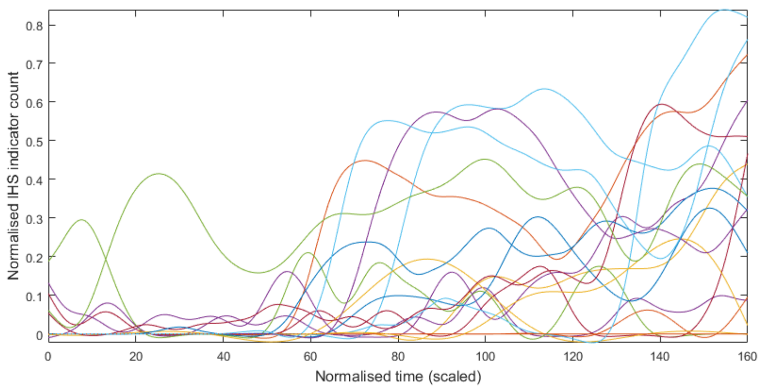


Figure 5.52: Functional Data Object for all technology profiles during the emergence stage based on *non-corporates by priority year*

5.9.2 Assessing the fit of generated functional data objects

Having created a functional data object representation of each model component from the selected bibliometric subset, the MATLAB script assesses the fit of each functional data object to the trend data. This is accomplished by calculating the residuals, variance, and standard deviations between the real and modelled values across the technology curves included, and across the time span of the TLC stage

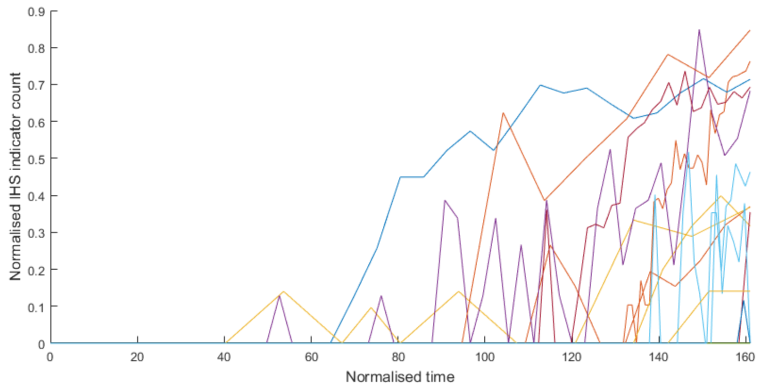


Figure 5.53: Technology profiles for *cited references by priority year* during the emergence stage

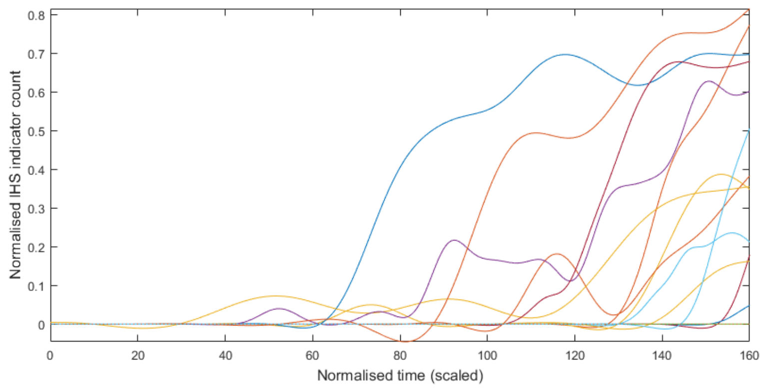


Figure 5.54: Functional Data Object for all technology profiles during the emergence stage based on *cited references by priority year*

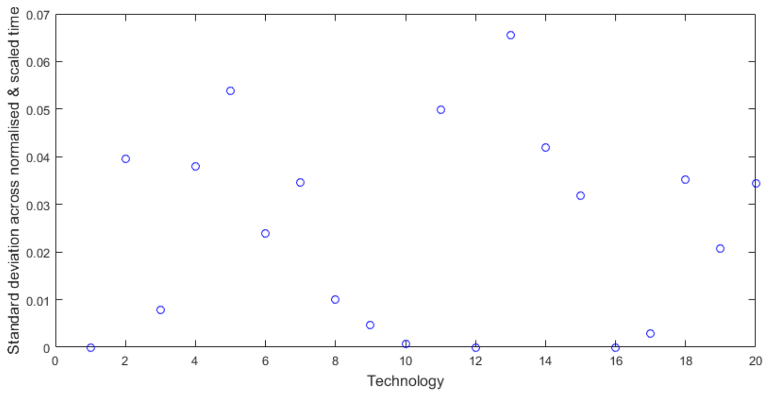


Figure 5.55: Standard deviations of the residuals within technologies from the functional data object for *non-corporates by priority year* (emergence stage)

considered (see section 5.5 of [Ramsay et al., 2009]). The results of this evaluation of fit are presented in Figs. 5.55 to 5.58 for the *number of non-corporates* and the *number of cited references* by priority year.

When considering the fitted curves one technology at a time, Figs. 5.55 and 5.56 show that the residuals associated with individual technology functions are all usually within 10% of the actual data points that

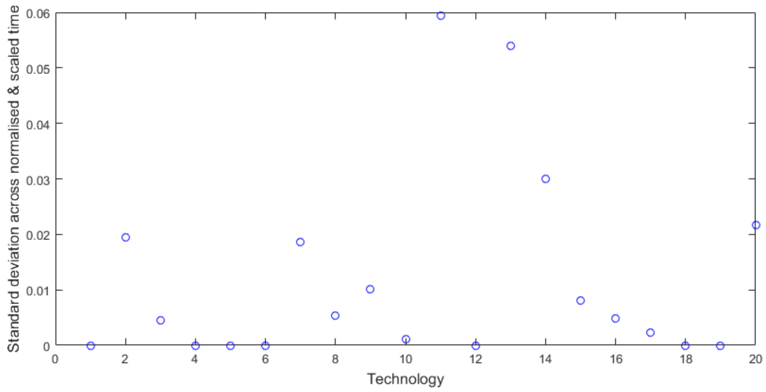


Figure 5.56: Standard deviations of residuals within technologies from functional data object for *cited references by priority year* (emergence stage)

they are modelling. For the vast majority (with only a handful of outlier technologies), the root-mean-square error (RMSE) is less than 5%. With the exception of technology 13 (nuclear energy), no other has a RMSE greater than 5% for both *non-corporate* and *cited references* model components, although the RMSE values for this technology still appear reasonable. As such, the distributions appear to show a good functional fit has been achieved on a technology-by-technology basis.

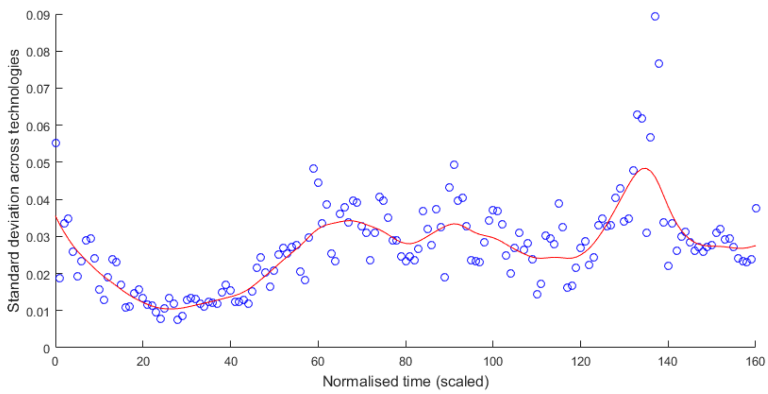


Figure 5.57: Standard deviations of the residuals within time from the functional data object for *non-corporates by priority year* (emergence stage)

Similarly, Figs. 5.57 and 5.58 show that RMSE values remain below 5% for the majority of time instances across the spread of technologies. Fig. 5.58 shows that there is some under and over prediction of the normalised count values for *cited references* occurring as the emergence stage progresses (i.e. the oscillating behaviour visible in the standard deviation trend line), leading to the standard deviation edging slightly higher than 5% for some time steps towards the end of the emergence phase. This is most likely due to the degree of smoothing applied in the functional curves fitted to the original data, and the associated derivative constraints that restrict the fit from following each time series exactly. However, the smoothing value was based on trying to provide the best out-of-sample predictive capability, to avoid over-fitting subsequent models to the existing data (see section 5.9.1). Therefore whilst it may be possible to reduce residuals and RMSE values further, it is likely that doing so would reduce the generalisability of the technology classification model. In terms

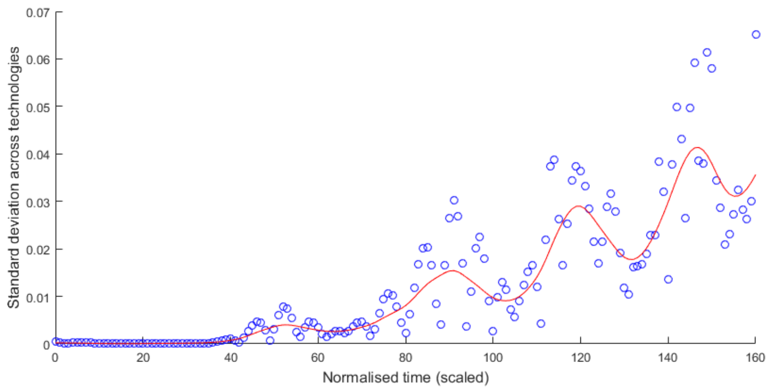


Figure 5.58: Standard deviations of the residuals within time from the functional data object for *cited references by priority year* (emergence stage)

of modelling implications, this increase in standard deviation represents an increase in variance for predicted values of *cited references* as the emergence stage progresses. This suggests that the corresponding functional data object (with the current level of smoothing), shown in Fig. 5.54, may not be satisfactory for accurately extrapolating the volume of cited references beyond the emergence phase. However, this trend is also partly apparent because the standard deviation is practically zero at the start of the emergence stage (in comparison to the equivalent standard deviation for *non-corporates by priority year*, in Fig. 5.57), due to the universal absence of cited references at this point (see Fig. 5.53). In this sense, the end of the emergence phase could also be converging towards normal variance levels, as the magnitudes are similar to those observed in Fig. 5.57. Nevertheless, the standard deviation levels appear reasonable for the emergence phase, and it is thought unlikely that the low RMSE percentages in Fig. 5.58 would adversely affect the classification model developed in this chapter. More specifically, the current model categorises technologies solely on data from the emergence stage, so no additional extrapolation is required to determine technology labels. This is more representative of real-world commercial applications, where it is likely that the available data for technologies of interest will be limited to earlier stages of development. The labels predicted in this analysis are subsequently used to select values of user-defined diffusivity and technological anomaly input parameters in the system dynamics model developed in chapter 6. Consequently, the system dynamics model does not use any further extrapolation of these input values after the emergence phase either. Instead, the dynamics predicted beyond this point are driven by diffusion equations, calibrated separately to observed adoption patterns for the substitution modes considered.

5.9.3 Functional descriptive statistics for generated functional data objects

An additional check of the functional data objects generated for use in functional linear regression is the plotting of descriptive statistics (see section 6.1.1 of [Ramsay et al., 2009]). The functional mean and standard deviation of the data objects (i.e. solid and dashed lines) for the *number of non-corporates* and the *number of cited references* by priority year are shown in Figs. 5.59 and 5.60 respectively. These figures show that for both model components, variation from the mean generally increases towards the end of the emergence stage (as may be expected from the spread of technologies and industries). For the two patent indicators plotted, the standard deviation indicates that once these technologies begin to emerge, the rate of growth observed for each metric varies significantly between technologies. In addition, mean functional data object values show that there is often an early surge, followed by a dip, in *non-corporates by priority year*, during the emergence phase before a technology achieves mainstream adoption. This potentially corresponds to the hype cycle associated with new technologies in early development, when significant levels of R&D may initially be committed to achieve commercialisation, which can sometimes prove premature or short-lived (see Fig. 2.4). By contrast, mean *cited references by priority year* values show a steadily accelerating growth during the emergence phase, without significant fluctuation, potentially implying that scientific development efforts are less sensitive to disturbances as they accumulate.

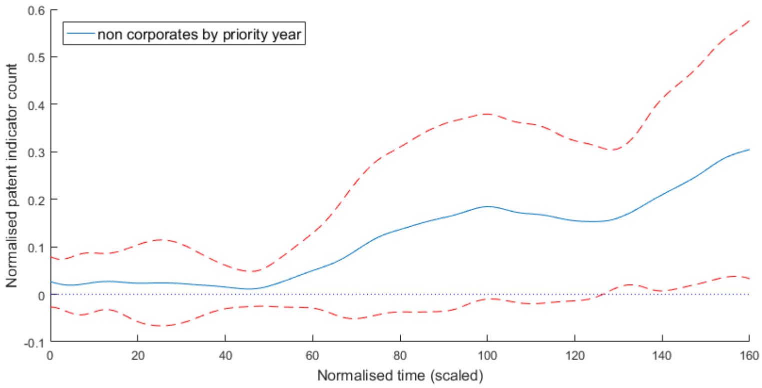


Figure 5.59: Mean and standard deviation of functional data object values for *non-corporates by priority year* (emergence stage)

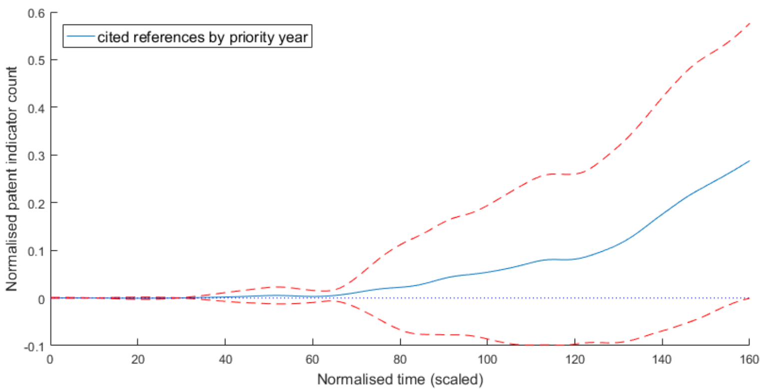


Figure 5.60: Mean and standard deviation of functional data object values for *cited references by priority year* (emergence stage)

5.9.4 Identification of smoothing parameter values for regression coefficients

With the functional data objects for each model component created, a cell array containing these components along with a constant predictor term (i.e. a cell array equal to 1 for all technology terms) is generated for use in functional linear regression. Before running the final regression analysis, a smoothing parameter for the regression coefficient basis system has to be selected. This is separate from the earlier parameter for smoothing technology profiles; this second parameter only addresses the roughness of regression coefficients. This is necessary to prevent over-fitting, and ensure that functional linear regression converges on a model that has the best chance of performing well out-of-sample when extended to future datasets. This smoothing parameter is selected by calculating leave-one-out cross-validation scores (i.e. error sum of squares values) for functional responses using a range of smoothing parameter values, as per section 9.4.3 and 10.6.2 of [Ramsay et al., 2009]. The results of this cross-validation exercise are shown in Figs. 5.61 and 5.62 for the *number of non-corporates by priority year* beta basis system smoothing parameter during the emergence phase. The functional parameter object for the regression coefficient basis system is then redefined using this more optimised smoothing parameter value.

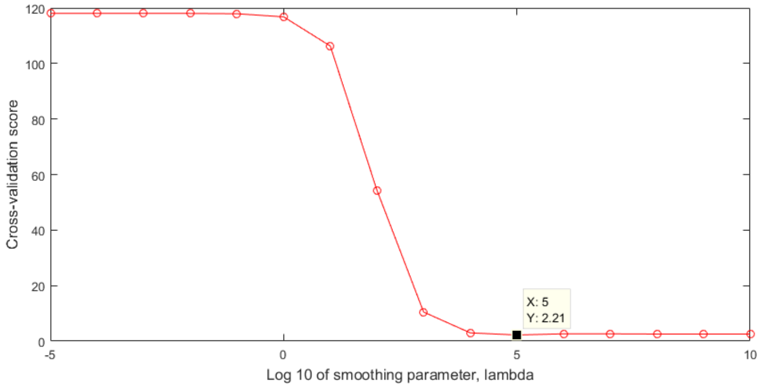


Figure 5.61: Cross-validation scores for the *non-corporates by priority year* beta basis system smoothing parameter (emergence stage)

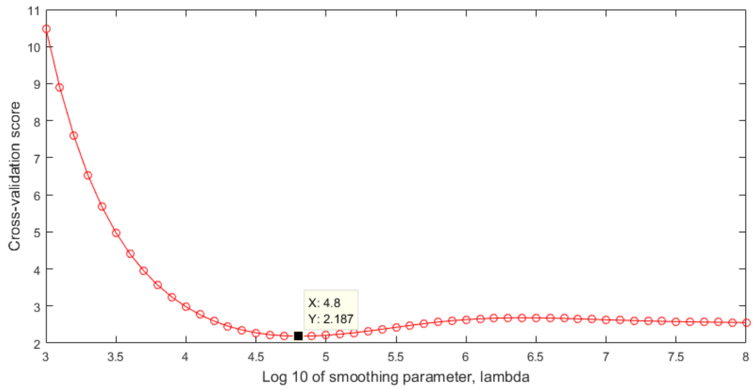


Figure 5.62: Refined cross-validation scores for the *non-corporates by priority year* beta basis system smoothing parameter (emergence stage)

5.9.5 Functional linear regression analysis

The functional linear regression analysis can now be run with the identified smoothing parameters and scalar response variables to identify the β_i coefficients and corresponding variance (used to define the

95% confidence bounds; see sections 9.4.3 and 9.4.4 of [Ramsay et al., 2009] respectively). Figs. 5.63 and 5.64 show the resulting β_i coefficients and confidence bounds (solid and dashed lines respectively) for the number of non-corporates and cited references by priority year during the emergence phase when using a high-dimensional regression fit (i.e. when the beta basis system for each regression coefficient is created from a large number of B-splines). In the high-dimensional model, the constant regression coefficient settles on a value of 0.0071. Figs. 5.63 and 5.64 meanwhile show that values of the β_i coefficients and 95% confidence limits calculated for the two selected patent indicators change continuously with time during the emergence stage. Based on these coefficient functions the regression fit successfully identifies the correct mode of substitution, from patent data available in the emergence stage, for 19 of the 20 technologies considered, as summarised in Table 5.6. Therefore on preliminary inspection, this time-based classification model appears to provide a good degree of accuracy. However, further investigation is required to ensure the model is not over-fitted, and that the result is not simply a naturally occurring phenomenon. For this reason, goodness-of-fit measures, benchmarking, and permutation testing are examined later in this analysis.

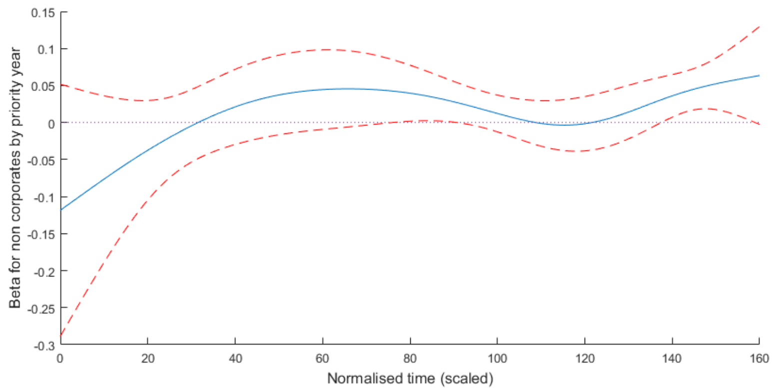


Figure 5.63: High-dimensional estimate of the regression coefficient for *non-corporates by priority year* during the emergence stage

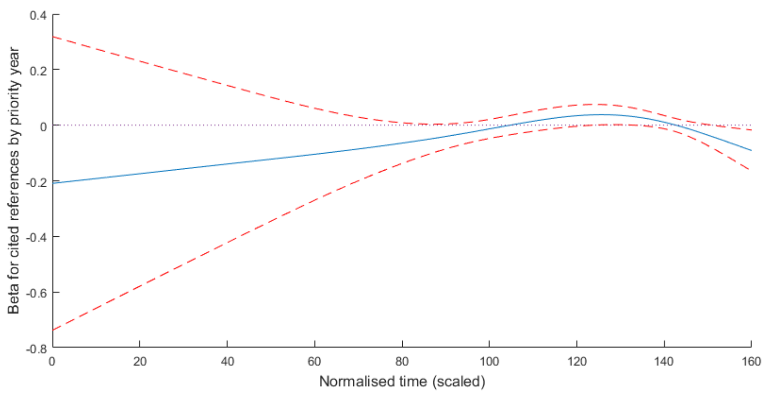


Figure 5.64: High-dimensional estimate of the regression coefficient for *cited references by priority year* during the emergence stage

Returning to the confidence bounds on these plots, it can be seen that for both the *number of non-corporates* and *cited references* that variance is highest at the start of the emergence phase. This is typically when the least amount of data is available for comparing each technology, and also when development activity is most sporadic, which is unsurprising as this represents the point of greatest uncertainty. Consequently, the confidence intervals suggest that the largest uncertainty around derived regression coefficients occurs at this point, particularly in the case of cited references (see Fig. 5.64). As time advances and more patent data becomes available, confidence bounds tighten around both of the calculated functional regression coefficients. About 60% of the way through the emergence phase, the confidence bounds for the two model components have both narrowed to what appears to be near their minimum bandwidth. This possibly infers that any real-time classifications made after this point may be converging towards their final predicted label, although the limited number of technologies considered makes this difficult to verify for more general applications. What convergence does occur is observed in more detail for the current technologies in Fig. 5.65, by plotting the inner product of the patent indicator counts and regression coefficients over time. Taking time series segmentation a step further, these results and the successful use of segmentation in this analysis suggest that future extensions to real-time applications may be possible.

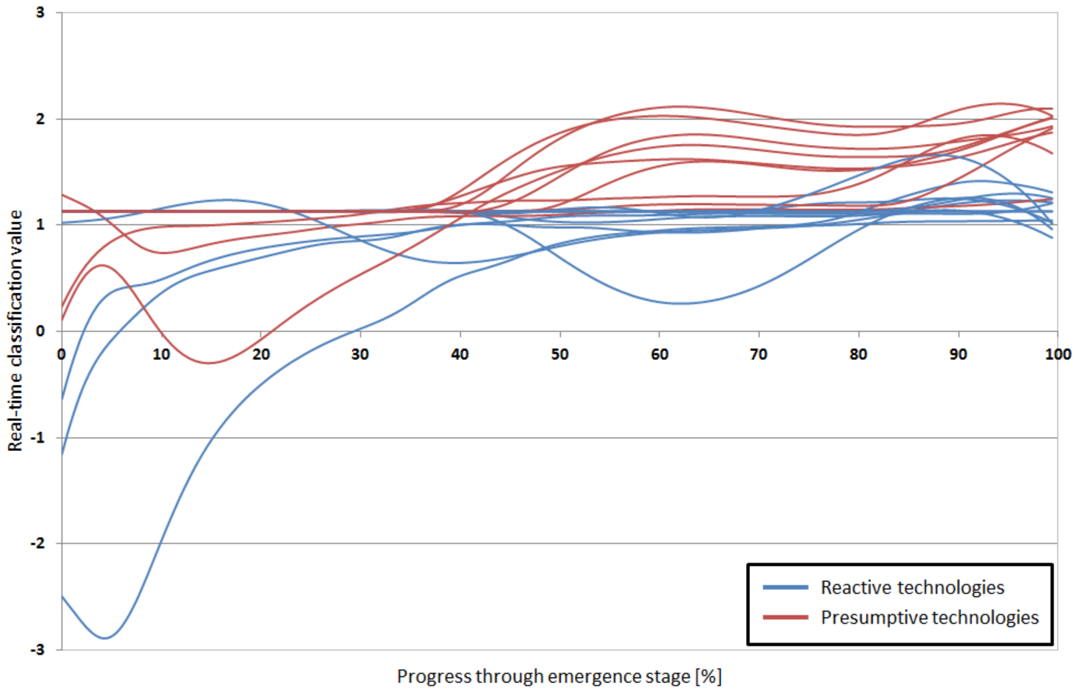


Figure 5.65: Real-time classification values (i.e. inner product of patent count and regression coefficient values) vs. progress through emergence stage

Figs. 5.63 and 5.64 also illustrate how the relative importance of each patent indicator in determining the predicted mode of substitution varies in time throughout the emergence phase (based on the datasets used). However, no causal explanation for why they receive these relative weightings is directly provided by these functions. Deviations from zero in these coefficient functions represent an increased positive or negative weighting for the associated patent indicator count at that time, within the determination of the predicted mode of substitution. For example, Fig. 5.63 suggests that any patents registered to non-corporate assignees at $t = 0$ (assuming these are present) will have a more significant influence

Table 5.6: Results of high-dimensional model fit

Correct mode type	R^2	Adjusted R^2	Degrees of freedom 1	Degrees of freedom 2	F-ratio
19/20	0.7954	0.7713	7.7837	11.2163	5.6024

on the predicted classification than at any other point in the emergence phase. The regression results also suggest that the impact of non-corporate activity next peaks around 40% of the way through the emergence phase (potentially corresponding to the hype effect suggested by Fig. 5.59), and again at the end of the emergence phase. For the *number of cited references*, this regression model suggests that the times of greatest impact on the mode of substitution are at the very beginning and end of the emergence stage. However, the confidence bounds indicate that there is still a reasonable amount of variance at these locations for both patent indicators considered, so the determining factor in the final classification is most likely to vary between technologies. It is also worth remembering here that these interpretations are based on a limited number of technology profiles and industries, so equally it is possible that the features identified are specific to the technologies or industries considered, or are characteristic of technology outliers. However, cross-validation procedures have been applied at each stage of this process to develop a model with good out-of-sample predictive capabilities, so this risk is believed to be low. Ultimately however, these patterns would need to be verified against a greater set of technology profiles to confirm these interpretations.

Whilst these coefficient plots provide some indication of relative patent indicator count weightings as time progresses, the cumulative nature of the inner products in functional linear regression (see Eq. 4.3) means it is not possible to visually infer which mode the test technology is converging towards from the coefficients alone. This requires the corresponding patent indicator counts that the coefficient terms are multiplied by for specific test technologies (producing the real-time classifier plots shown in Fig. 5.65).

Regression coefficient plots help to provide a possible interpretation of relationships between each model component and predicted technology substitution modes. However, it is also necessary to check the *goodness-of-fit* measures associated with these results. As discussed in section 4.5, these common statistical measures examine the amount of variability that is explained by the current model, and test the likelihood that the same result could be obtained by chance. As such, *R-squared*, *adjusted R-squared*, and *F-ratio* statistics are calculated (see sections 9.4.1 and 9.4.2 of [Ramsay et al., 2009]) to assess the overall fit of the high-dimensional functional linear regression model. These are summarised in Table 5.6.

The R-squared and adjusted R-squared values in Table 5.6 suggest that a reasonable fit has been achieved with this model across the 20 technology profiles during the emergence phase. These values, which describe the proportion of variation that is predictable from the selected patent indicators, suggest a good level of accuracy based on the classification residuals. F-ratio values provide a measure of the variance observed between the two classification groups to the variance observed between individual technologies, taking into account the number of independent variables used in the model. In doing so, F-ratio values provide an indication of whether the classification grouping is significantly distinguishable from noise that might otherwise be observed between individual technologies. The degrees of freedom

Table 5.7: Benchmarking results

Model basis	Correct mode type	R^2	Adjusted R^2	Degrees of freedom 1	Degrees of freedom 2	F-ratio	p-value
Low dimension	19/20	0.8514	0.8340	10	9	5.1584	0.0107
Constant	18/20	0.6200	0.5753	2	17	13.8684	0.0003
Monomial	19/20	0.8139	0.7920	8	11	6.0139	0.0040

in Tables 5.6 and 5.7 are used to determine whether F-ratio values are above the critical F-ratio threshold, and are calculated based upon methods outlined for functional regression models in sections 9.4.1 and 9.4.2 of [Ramsay et al., 2009]. In this instance, the F-ratio of 5.60 with degrees of freedom 7.78 and 11.22 respectively implies that the relationship has a p-value somewhere between 0.0041 and 0.0060. As such, this result appears to be significant at the 1% level, meaning that it is unlikely that this classification label set would occur by chance. This compares well to the results of the cross-validation exercise outlined in section 5.8 for ranking indicator sets based on likely predictive performance.

5.9.6 Benchmarking functional regression model

To ensure that it provides the most appropriate fit to available data, the original high-dimensional model was subsequently benchmarked against a low-dimensional model (i.e. a model where the beta basis system for each regression coefficient consists of a small number of B-splines), as well as constant and monomial based models. These variants use the same patent indicator terms as the high-dimensional model, ensuring that only the regression coefficients are changed (based on the alternative B-spline basis systems used). The corresponding β_i coefficients from the benchmarking analysis for the low-dimensional model are presented in Figs. 5.66 and 5.67, whilst the 'goodness-of-fit' measures for the alternative functional linear regression models are compiled in Table 5.7. In the low-dimensional model the constant regression coefficient is found to have a value of 0.0075.

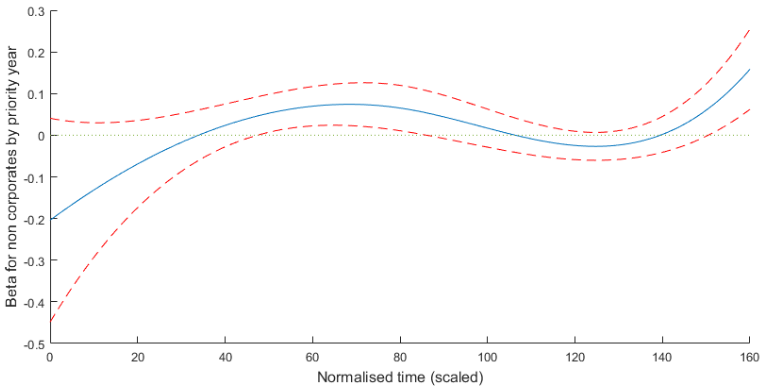


Figure 5.66: Low-dimensional estimate of the regression coefficient for *non-corporates by priority year* during the emergence stage

Whilst the R-squared and adjusted R-squared measures in Table 5.7 suggest that the low-dimensional model provides a better fit, the associated F-ratio score and corresponding p-value suggests a lower significance than the values observed for the high-dimensional model. Conversely, the constant basis

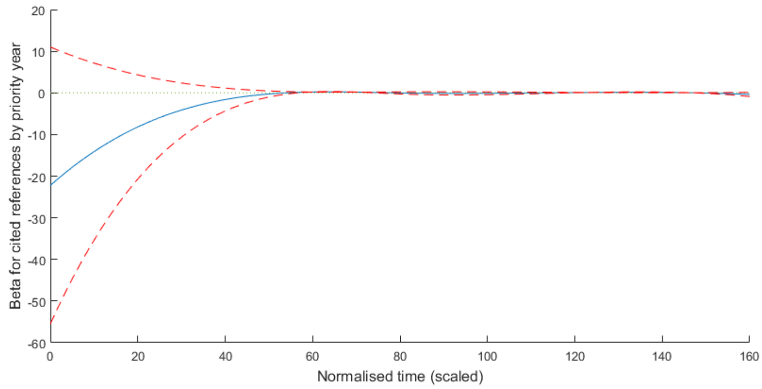


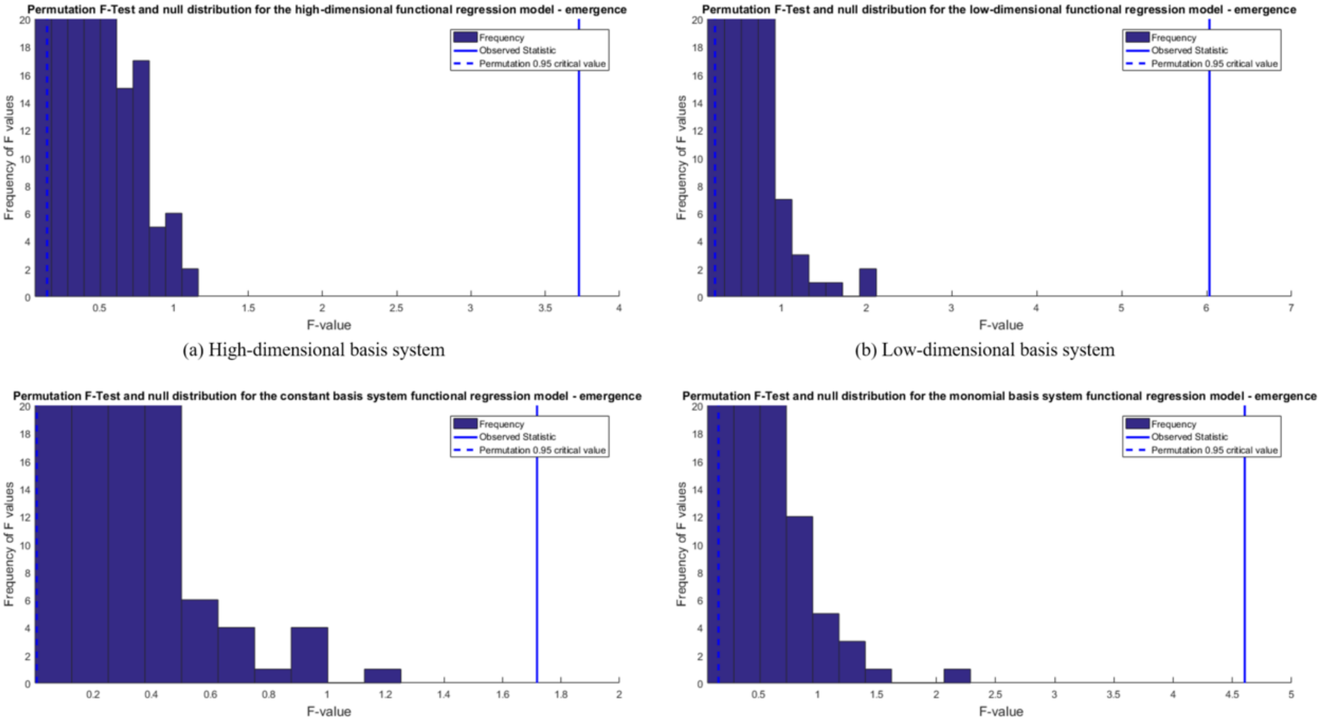
Figure 5.67: Low-dimensional estimate of the regression coefficient for *cited references by priority year* during the emergence stage

model does not appear to provide as good a fit to the expected scalar responses from the R-squared and adjusted R-squared values, which is not surprising considering the more limited nature of models constructed from constant terms. Finally, the monomial basis system performs fractionally better on both the R-squared and adjusted R-squared measures, whilst also achieving a comparable level of significance to the high-dimensional model. Consequently, this benchmarking analysis suggests that the high-dimensional and monomial basis system models are the most suitable candidates. However, the performance of the models could possibly be further improved by sensitivity studies into the optimum number of knots and order of the B-splines to use in the regression fit.

5.9.7 Permutation testing of functional regression models

To further validate the statistical significance of the four models, permutation testing counts the proportion of generated F values that are larger than the F-statistic for each model (see section 9.5 of [Ramsay et al., 2009]). This involves repeatedly shuffling the expected mode classification labels versus the technology profiles being read (maintaining their original order) to see if it remains possible to fit the regression model to these reordered responses. This tests the sensitivity of the predicted classification labels to the order that the technology profiles appear in, to examine how the results would appear if there was no relationship between the derived classification functions and original data. In doing so, this test also creates a null distribution versus the q^{th} quantile and observed F-statistic generated from the models themselves. The results of this analysis are shown in Fig. 5.68.

For statistical significance it is necessary that the observed test statistic (shown as a solid blue line) is in the tail of the distribution generated, implying that predicted classification responses would only occur very rarely (i.e. not by chance) if the data was rearranged. Having generated classification models based on the most robust predictors from the earlier cross-validation exercise, all four models suggest that a significant relationship has been identified between expected substitution mode predictions and the two patent indicator dimensions used, that is specific to the data provided. However, as seen in Tables 5.6 and 5.7, the fit achieved varies depending on the model used. As such, these distributions appear to reinforce the significance of the patent indicators selected from the earlier clustering and



(a) High-dimensional basis system

(b) Low-dimensional basis system

(c) Constant basis system

(d) Monomial basis system

Figure 5.68: Permutation F-Test and null distribution for functional regression model variants (emergence)

ranking exercise. Additionally, the permutation testing in this last stage of analysis reveals that the high and low-dimensional model variants are likely to perform best out-of-sample as the observed F-statistics are furthest along each distribution's right tail, when compared to the distributions generated for the constant and monomial based models. This indicates that results from these two models have the lowest probability of occurring by chance, and are most likely to be generalisable to future datasets. A similar level of statistical significance is observed between the high and low-dimensional models, although as permutation testing was only based on 1,000 permutations, there is scope for the distributions to evolve further with more permutations. However, the constant basis system model appears not to perform as well out-of-sample here, with the observed F-statistic closest to the main body of the distribution. This, in combination with the other 'goodness-of-fit' measures in Tables 5.6 and 5.7, suggests that the high-dimensional functional linear regression model provides the best basis for a technology substitution classification model, based on the selected patent indicators, from those tested in this analysis.

5.10 Conclusions from statistical ranking and functional data analysis

Expanding on previous historical accounts of technological substitutions, this chapter has outlined a new methodology for automatically classifying the dynamics observed in substitutions, based on patterns identified in scientific and technological development. This builds on the conceptual framework outlined by Ron Adner that defines technological substitutions in two dimensions which describe the *emergence challenges* facing new technologies and the *extension opportunities* still available to existing technologies (see section 2.5). The analysis in this chapter has focused on the *extension opportunity* dimension of this framework to facilitate the translation of Adner's work into a repeatable and generalisable method for automatically detecting substitution modes. From this, two substitution modes appear to correspond to significantly different technology adoption characteristics (discussed in the next chapter), with scientific foresight believed to play a crucial role in the identification of presumptive innovations, and performance stagnation leading to reactive transitions.

As such, this analysis has considered 23 technologies where literature evidence of performance development trends has been found, to test the ability to correctly identify associated adoption modes using bibliometric, pattern recognition, and statistical analysis techniques. This is achieved via a two stage process, where the patent indicators most likely to produce a reasonable basis for Adner's classification scheme are identified by an initial clustering and ranking analysis, before time dependent patent indicator models (for use in subsequent causal analysis) are constructed from functional linear regression. This allows variation specific to individual patent indicators to be considered separate from phase variation observed between technologies. The results obtained suggest that statistical analysis of patent indicator time series, segmented according to identified Technology Life Cycle features, provides a possible means for automated classification of technological substitutions using Adner's framework. Specifically, for the datasets considered, measures of the number of cited references and involvement of non-corporate entities by year during the emergence phase were found to provide a good indication of the expected mode of substitution when used as a basis for functional linear regression (correctly classifying 19 out of 20 technologies included in this stage), and performed consistently well in statistical ranking of both in and out-of-sample predictive capability. The selected patent data dimensions can be associated with perceptions of scientific and technological production respectively, consistent with the prerequisites listed in section 2.9 for a classification scheme that can recognise reactive and presumptive technological substitutions.

Whilst these two patent metrics occur in all of the most robust predictor subsets (i.e. in terms of out-of-sample reliability) when basing analysis on the emergence stage, this does not prove that these are the only indicators capable of predicting substitution modes. As discussed in section 5.9, the possibility of orthogonality has not been ruled out for the other patent indicators in Table 5.1. However, these two dimensions are also in good agreement with the technological anomaly arguments put forward by Constant in sections 2.2 and 2.5, and so were felt to be reasonable for forming the basis of the time-based classification model that has been developed using functional linear regression. Subsequently, a regression fit made from beta coefficient functions with many B-spline elements was found to provide a viable means of correctly matching the mode of substitution to the technology profile being evaluated when considering multiple 'goodness of fit' measures.

Permutation testing of the time-based classification model further suggests that the regression fit is sensitive to the ordering of the expected mode labels, relative to the technology time series being considered. The relationship observed appears therefore to be based on the specifics of the individual technology curves considered, and does not appear to occur by chance. This in turn implies that it may be possible to predict modes of substitution using Adner's framework from limited bibliometric data during the earliest stages of technology development, providing some evaluation of progress through the early stages of the Technology Life Cycle is made (this can be obtained using a nearest neighbour matching process, discussed in section 5.5). Equally, this suggests that the functional regression corroborates the earlier statistical rankings produced using Dynamic Time Warping, K-Medoids clustering, and leave-one-out cross-validation leading to the selection of patent indicators, providing evidence of compatibility between the methods used in this analysis.

It is also important to remember the potential limitations of this study, which would need to be addressed for further confidence in the methodology. Firstly, only a relatively small number of technologies have been evaluated here due to the time-consuming process required for data extraction, preparation, and identification of supporting evidence from literature for the assignment of expected classification labels. Consequently, whilst precautions have been taken to minimise the risk of model over-fitting, the cross-validation procedures employed would benefit from further verification with a more diverse spread of technologies to ensure that out-of-sample errors are accurately captured. Regression models based on small sample sizes can be very fickle to the datasets they are calibrated to, so it cannot be ruled out that the results obtained are a better fit to the industries included, rather than a model that can be generalised to all technologies. For the same reason, this analysis should be extended to different types of technology profiles, such as non-starter technologies (see section 2.5.8), to ascertain whether the methodology is able to recognise differences between commercially successful and 'failed' technologies.

However, perhaps the most important note of caution regarding this classification model relates to the quantitative approaches used. Whilst statistical approaches are well-suited to detecting underlying correlations in historical and experimental datasets, this on its own does not provide a detailed understanding of the causation behind associated events. This is particularly relevant when considering the breadth of reasons for technological stagnations, 'failures', or presumptive leaps. Equally, statistical methods are not generally well-suited to predicting disruptive events and complex interactions; other simulation techniques such as system dynamics and agent based modelling perform better in these areas. Accordingly, to identify causation and test the sensitivity of technological substitution patterns to variability arising from real-world socio-technical behaviours not captured in simple bibliometric indicators (such as the influence of competition, and more tightly focused organisational and economic effects), the fitted regression model also needs to be evaluated from a causal perspective.

Similarly, to demonstrate practical applicability, the mode of substitutions considered here based on Adner's classification scheme need to be related to observed adoption characteristics (discussed in chapters 2 and 6). Consequently, a system dynamics model built on the regression functions identified in this study is proposed (discussed in the next chapter), to calibrate these extracted technology profiles and mode predictions to empirical adoption data. This aims to more thoroughly explore the causal mechanisms relating early indicators of technological substitution to the eventual adoption patterns observed, and provide a means of applying greater reasoning to the relationships identified here.

Chapter 6

Implications for technology adoption forecasting

In this chapter, outputs from the technology classification model presented in chapter 5 are considered in relation to forecasting technology adoption behaviours. To begin with, market share data for the technologies of interest is presented, as extracted from the data sources listed in chapter 4. This is followed by an examination of the weighted patent indicator functions generated in chapter 5 for the technologies considered in the diffusion model. Subsequently, an illustration is provided of how a system dynamics model could be structured and calibrated, based on the findings in chapters 2 to 5, to provide a forecast of adoption trends for the two modes of substitution considered (following studies combining bibliometric and system dynamics approaches, such as the work of Daim et al. [Daim et al., 2006]). The results and conclusions from this analysis, with recommendations for future work, are then considered at the end of this chapter.

6.1 Historical technology adoption profiles and trends

Following the review of event timelines for extracted patent profiles (see chapter 5), the corresponding market share data is now presented for the technologies of interest. The data sources in Table 4.1 of chapter 4 have been used to compile the datasets presented in Figs. 6.1 to 6.8. Where possible, market share data representing global trends has been used, although in instances where global datasets were not available, localised adoption data is provided to represent typical adoption trends. This is detailed below for the technology groups considered. For much of the data presented (including all International Energy Agency, OECD, UN, and World Bank data sources), data was extracted using the online *UKDS.Stat* platform.

6.1.1 Domestic lighting technologies

A range of comprehensive 'Mapping and Benchmarking' reports have been compiled on the state of domestic lighting for numerous countries around the world, as part of the International Energy

Agency's technology collaboration programme on Energy Efficient End-Use Equipment (4E) [International Energy Agency 4E, 2014]. Accompanying these reports, datasets have been compiled for each of the countries participating in the technology development programme, although a combined global view has not been generated from these datasets. Merging datasets from different geographic regions can present considerable risks if appropriate weightings are not assigned to each set of values. As such, the decision was taken here to select a single country from those in the IEA 4E reports to represent global trends observed in domestic lighting markets, rather than attempting to combine the existing datasets into an approximated global picture. Accordingly, Fig. 6.1 displays the adoption trends in the IEA 4E report for the UK domestic lighting market between 1999 and 2013. The UK market was selected as the reference as the IEA report noted that the values quoted were verified against annual sales data, and were considered to provide a relatively robust view of the complete domestic lighting market for residential properties [International Energy Agency 4E, 2014]. In addition, as the UK was one of the signatory countries to the enforced phase-out of incandescent lights from 2010, the trends presented are considered to be at the forefront of the global shift away from filament based lighting technologies, so demonstrate one of the earlier substitutions observed. A notable feature of the data is the spike in CFL sales in the UK between 2008 and 2010, which is presumed to result from the UK Carbon Emissions Reduction Target policy that led to utility companies distributing large numbers of CFL bulbs during this period. Further details relating to the collection and aggregation of this data are provided in the UK mapping and benchmarking report [International Energy Agency 4E, 2014], whilst actual trend values are tabulated in Appendix E.

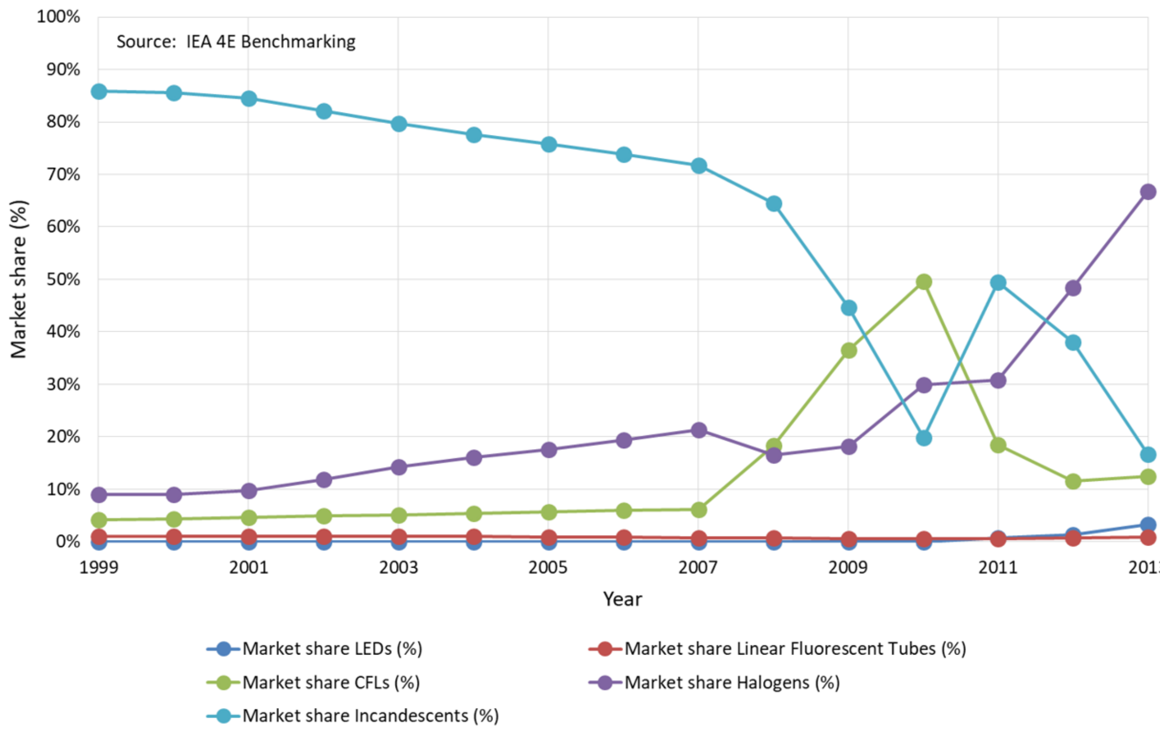


Figure 6.1: UK lighting market share by technology between 1999 and 2013

6.1.2 Electric vehicles

Electric vehicle market share values are based on Eurostat's data for new registrations of passenger cars in the EU by: motor energy and engine size between 1970 and 2013, registrations of alternative motor energy vehicles between 1987 and 2012, and records in the ICCT's European Vehicle Market Statistics Pocketbook for 2001 to 2015 [Eurostat, 2017, The International Council on Clean Transportation, 2016]. The ICCT data, which is in very good agreement with the Eurostat data on EU market sizes and electric vehicle registrations, enables the Eurostat dataset to be extended from 2012 to 2015. From this, the combined market share of both Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV) in the EU is obtained between 1987 and 2015, as shown in Fig. 6.2. Tabulated data for these trends is provided in Appendix E.

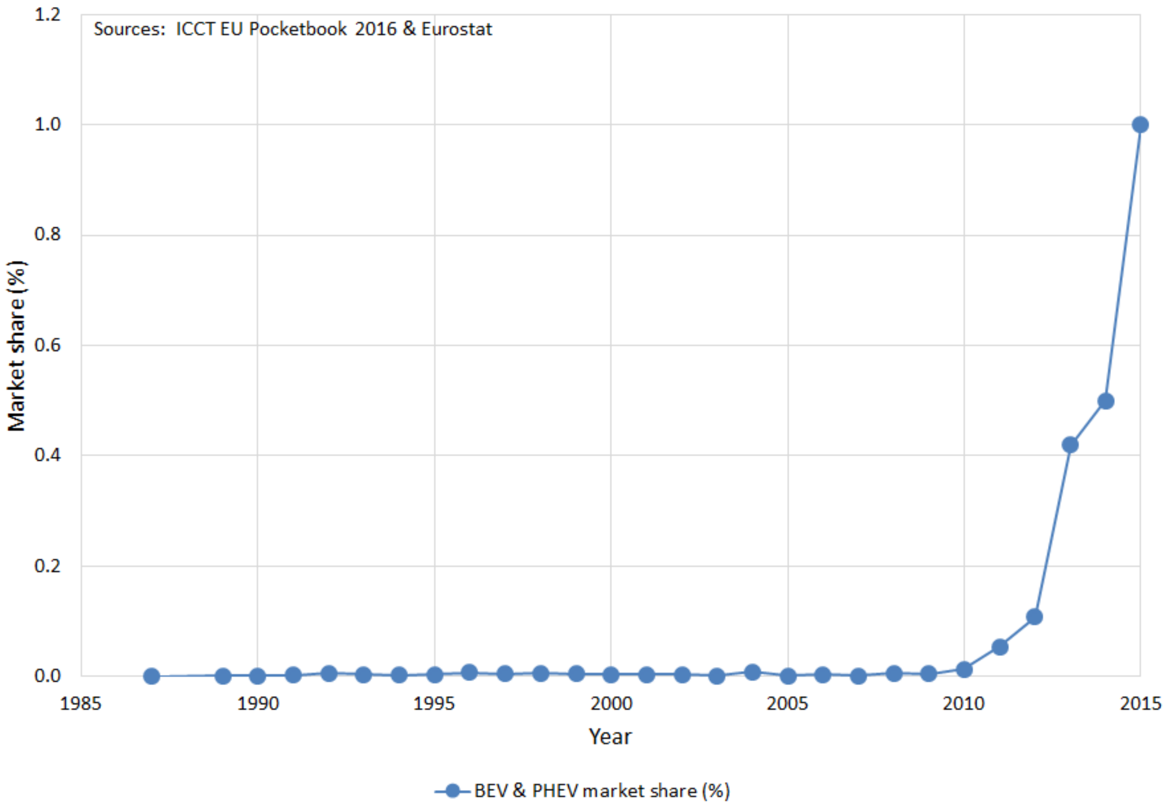


Figure 6.2: Electric vehicle market share in the EU between 1987 and 2015

6.1.3 Personal printer technologies

As global and regional shipment data for personal printer technologies is not readily available, several data sources are combined here to depict market share trends for the four printer technologies considered (Fig. 6.3). The printer shipment values used to construct these trends are based on recorded U.S. shipment data, except where forecast approximations are used instead to represent market share values (hollow data points in Fig. 6.3). In both cases, market share values have been identified from magazine articles, although these sources in turn quote figures from either International Data

Corporation or BIS Strategic Decisions analysis (see Table 4.1 in chapter 4 for details of these). Therefore the magazine sources present a consistent account of market share trends as they reference the same original sources and reports. For most years considered, it was possible to obtain market share values for all printer technology types, however in some cases values were only supplied for one or two of the technologies. On these occasions, only the known technology values are plotted. Where approximate values are reported, these are based on forecast projections of market share shipments at the time, from the number of installed units in the U.S. Many of these forecast values complete gaps of missing years, and therefore sit between known values. Consequently, these projected values appear reasonable when compared to the known historical data points, as they agree with already observable trends from the fixed data points (shown in Fig. 6.3). Similarly, the U.S. market share data points for 2012 to 2015 are based on the quoted number of installed printer types worldwide, as IDC shipment records were not identified beyond 2009. However, these values follow existing trends and historical events (see section 5.5.12 in chapter 5 on the history of laser printer development, detailing the resurgence of laser printers following early market dominance of inkjets), and agree with market share values from Forbes in 2015 [Forbes, 2015]. For further details, tabulated data and comments on individual data points are in Appendix E.

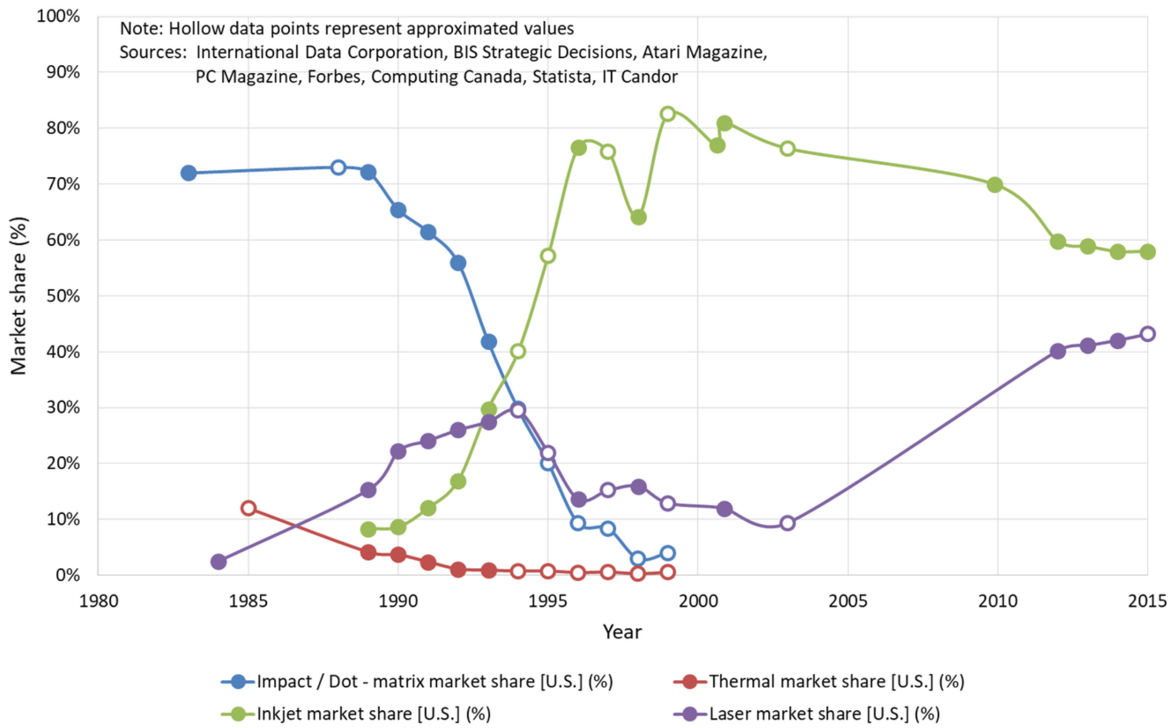


Figure 6.3: U.S. market share for personal printer technologies between 1983 and 2015

6.1.4 Renewable electricity generation sources

The International Energy Agency's *World Energy Statistics* database has been used to extract the renewable electricity generation adoption trends observed between 1971 and 2014, as shown in Figs. 6.4 and 6.5 [International Energy Agency, 2016]. This database provides a comprehensive

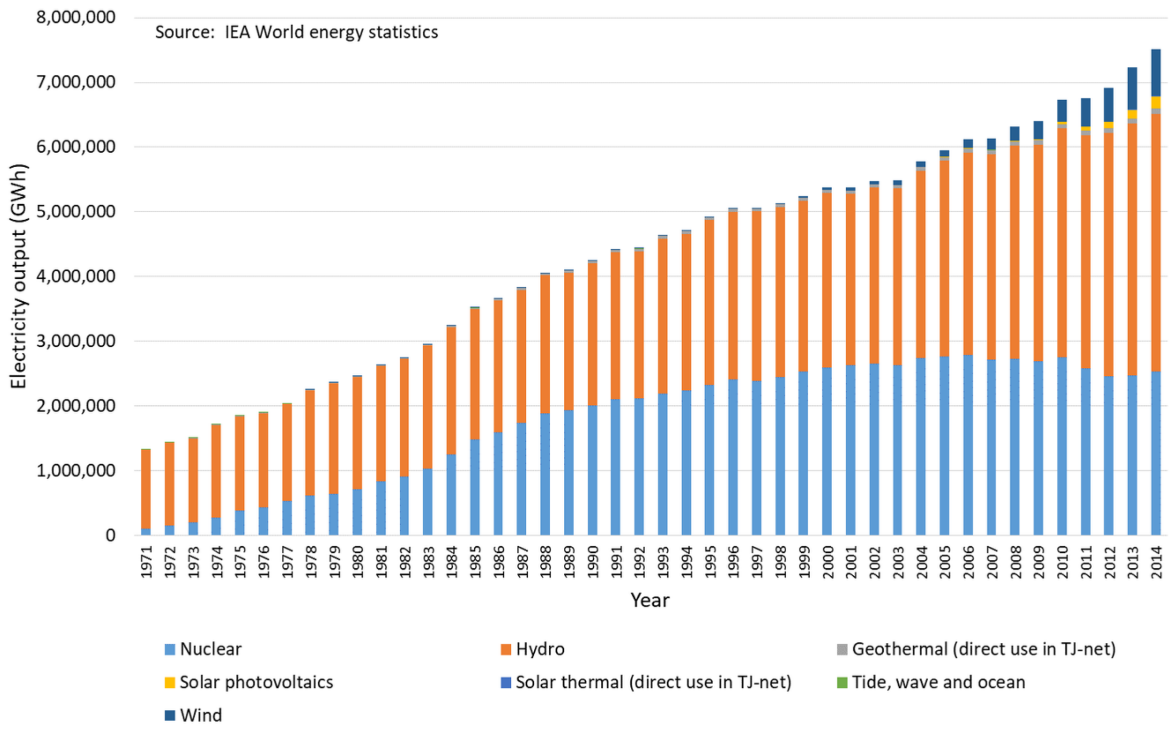


Figure 6.4: Global electricity output (GWh) from low-carbon generation sources between 1971 and 2014

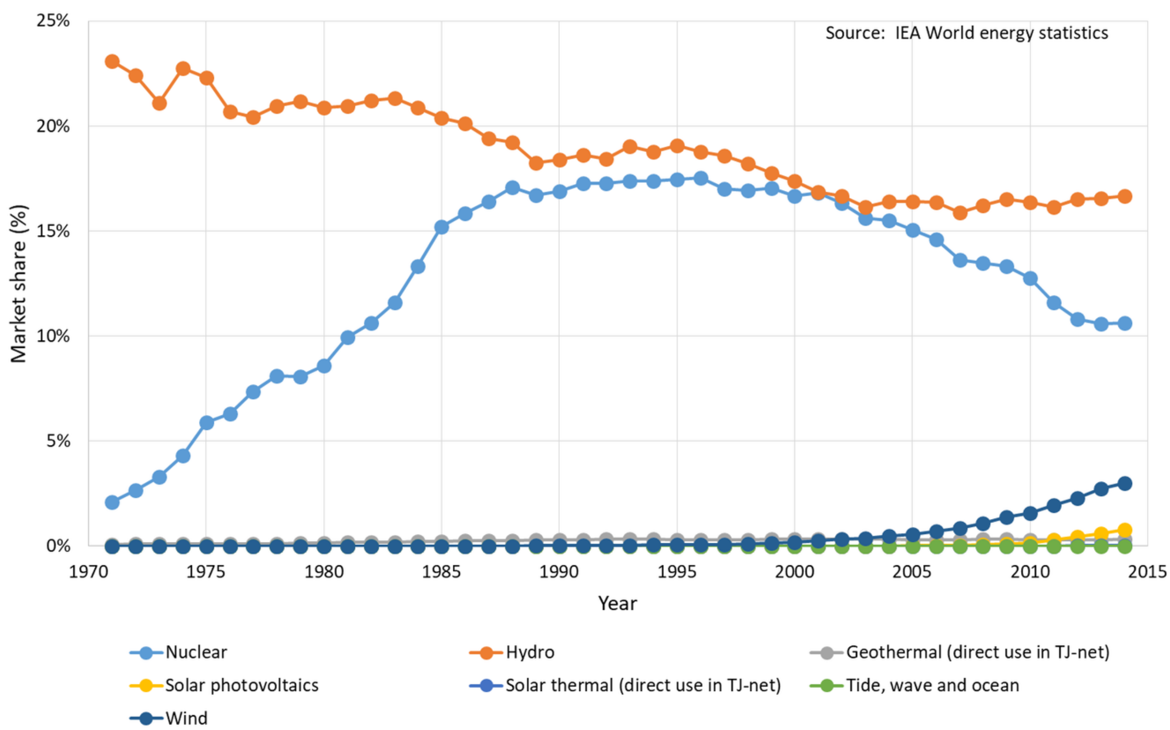


Figure 6.5: Global market share for low-carbon electricity generation sources between 1971 and 2014

summary of world energy production and consumption, regarding both heating and electricity usage, for all major forms of energy generation. However, to ensure that adoption trends are consistent with the historical review of performance characteristics used to determine the mode of substitution (detailed in chapter 2), only electricity generation data is used in the following analysis. Tabulated data is available for these renewable electricity generation sources in Appendix E.

6.1.5 Turbojets and jet propulsion

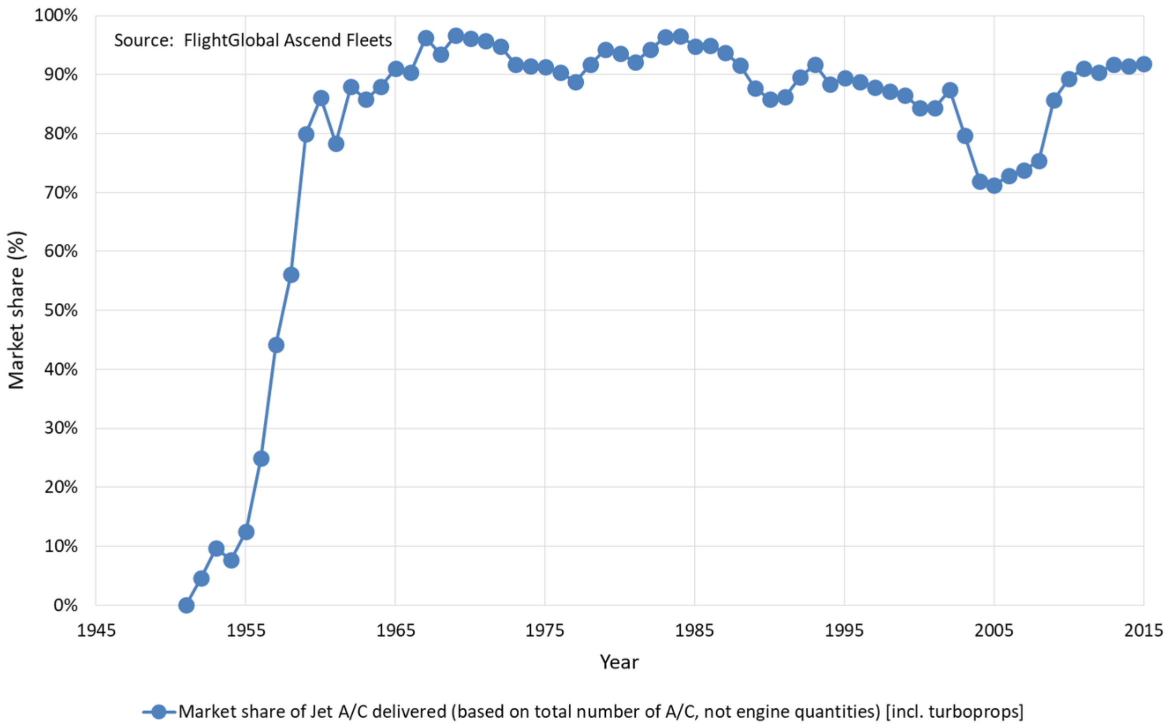


Figure 6.6: Global market share of jet aircraft in commercial and military deliveries between 1951 and 2015

Since their first development, turbojets have been deployed in a wide range of roles and markets (extending beyond air vehicles, although primarily in this domain). Driven initially by military developments, 'market share' for this technology extends beyond civilian products. As a result, it is difficult to ascertain an exact, or at least, consistent number of turbojet products that have been sold around the world following their initial entry into service. There is however, a clearer distinction between general and commercial aviation applications. By excluding general aviation trends, the Ascend Fleets database (managed by Flight Global) provides a consistent and credible source of both commercial and military aircraft transactions [Flight Global, 2017]. This database has therefore been used to extract details of fleet deliveries since 1951. By grouping the aircraft deliveries by market class, the Ascend Fleets data allows jet and piston aircraft deliveries within commercial and military sectors to be segregated. From this, the market share based on delivery trends is calculated (shown in Fig. 6.6). The impact of the terrorist attacks on the World Trade Centre in 2001 appears to have had a significant impact on jet aircraft deliveries around the world over the following three years (airline growth effectively stalled during this period), before the industry began to recover around 2005. This fragile recovery was weakened by the financial crisis of 2008, which effectively negated another two years of aviation growth [IATA, 2011]. Tabulated data is available for these recorded aircraft deliveries, with details of categories included within the jet and piston aircraft groups, in Appendix E.

6.1.6 Telecommunication technologies

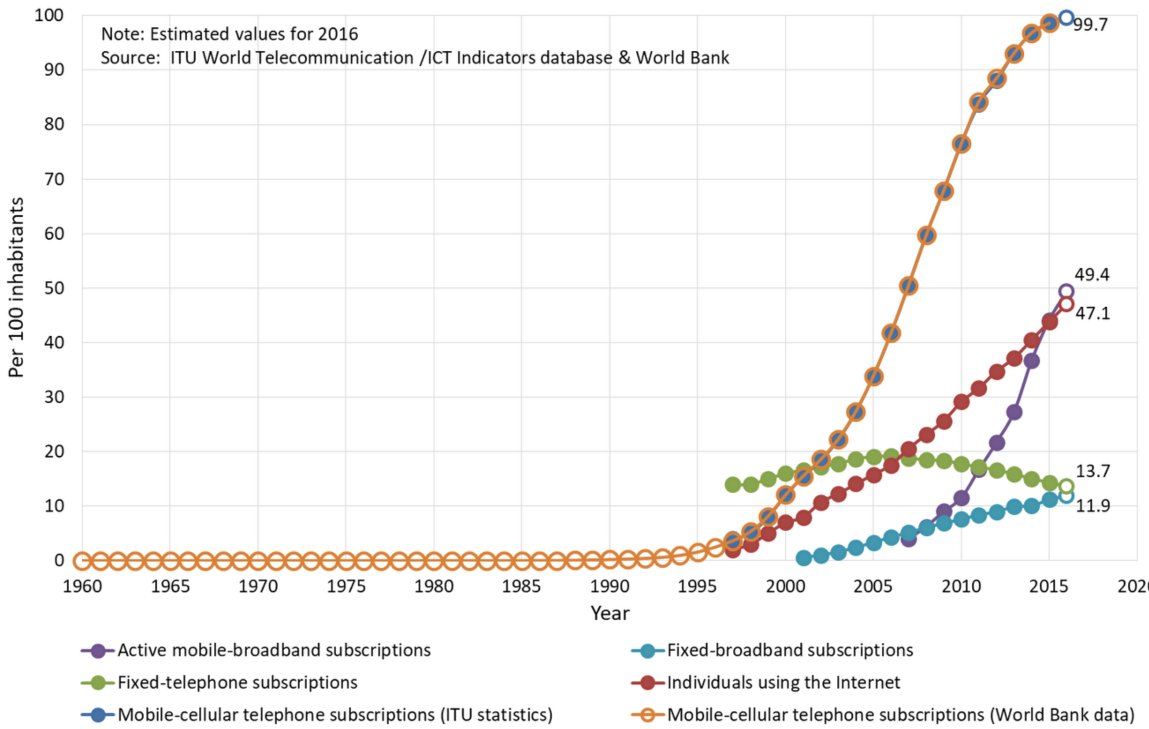


Figure 6.7: Global ICT market shares by technology between 1960 and 2016

For the telecommunication technologies of interest, data has been extracted from the ITU's *ICT Indicators database* and World Bank's *World Development Indicators* [International Telecommunication Union, The World Bank, 2017, Harris et al., 2000]. By extending ITU's Global ICT development data (from 2001 to 2016) with the mobile telephone subscriptions recorded by the World Bank since 1960 (which is effectively identical to the ITU values from the overlapping period), the market share trends in Fig. 6.7 were obtained. An important point to note is the use here of mobile telephone subscriptions as a proxy for measuring the market share associated with wireless data transfer. Although some data on wireless data transfer is provided by Cisco's VNI forecast data [Cisco Systems, Inc.], wireless data IP and internet traffic is not easily discernible prior to 2010, making it difficult to obtain a consistent market share trend. As a result, mobile phone subscriptions have been used to indicate the prevalence of wireless data transfer technologies, as mobile phones, and their dependency on packet switching, are widely regarded as the most visible component of wireless data technologies. It could also be argued that traffic alone does not provide a clear indication of technology penetration, as heavy traffic volumes can be generated by a small percentage of existing adopters from the global population (i.e. technology dependent nations), biasing the picture of technology dispersal towards this small population. The possibility of bias remains partially true of technology subscriptions, but to a lesser extent than overall traffic volumes. Tabulated data for the extracted telecommunication indicators is provided in Appendix E.

6.1.7 Market share characteristics for reactive and presumptive substitutions

By translating the market share trends in Figs. 6.1 to 6.7 on to a relative timescale (based on the year of the first recorded patent in the corresponding dataset - see chapter 5), and collating the data into respective substitution groupings, the adoption characteristics of reactive and presumptive substitution sets is explored, as displayed in Fig. 6.8. In this instance, reactive substitutions are in blue, with presumptive substitutions in red. The earliest priority year for the first patent entry in each dataset provides the basis for these timescales, as this gives a reasonable indication of when a product or technological application was first conceived. This also allows a reference time-frame to be applied consistently for technologies, even if the date of the original innovation (or insight that led to this) is unclear. This accords with the date of invention used in the study by Hanna [Hanna et al., 2015].

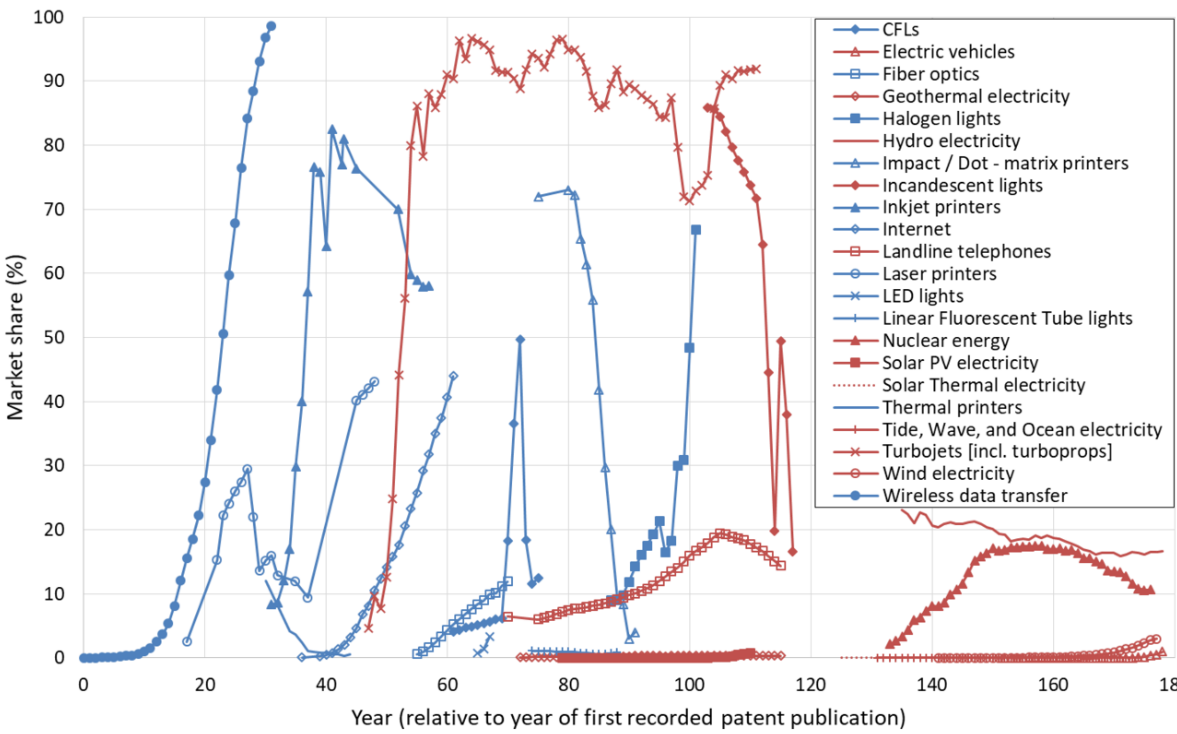


Figure 6.8: Adoption of technologies relative to year of first patent record in dataset

From this, the first observation is that there appears to be a clear distinction between relative take-off times associated with each group. Reactive technologies achieved commercialisation and significant market uptake typically at least twice as fast as the presumptive technologies considered. This puts into perspective the presumption and technological failure effects described in the literature. This is interesting for commercial applications, as it suggests that from knowledge of the first patent linked to an emerging technology, trends can begin to be predicted for typical development times expected for different substitution modes. The trends displayed here must be taken in the context of the limited sample of technologies examined, and in some cases the partially complete adoption curves. However, the preliminary results suggest that reactive substitutions experience accelerated uptake resulting from technological stagnation observed in the incumbent technology. It is also notable that with the exception of turbojets, reactive substitutions generally appear to have a much steeper rate of adoption following take-off than presumptive technologies. This is perhaps unsurprising, as in reactive conditions, demand for an urgent replacement is most pressing, whilst in presumptive substitutions, the necessity of the new technology is not immediately apparent. Turbojets are the obvious exception to this within the presumptive technologies considered, as their proliferation greatly accelerated due to military demands during World War II. Lastly, although in some cases mainstream adoption is captured by the extracted reactive and presumptive datasets, there is insufficient data here to comment on the prospects that one technology group is more likely than another to achieve eventual market dominance. This remains an area for future exploration as more data becomes available. It is also important to reiterate that these adoption trends are based on a small sample of technologies from a limited spread of industries, so these observations should be verified for a more diverse spread of technologies. These observations aside, for the purposes of this study, the data in Fig. 6.8 is subsequently used for the final calibration of the technology substitution model constructed in this chapter.

6.2 Evolution of the technology substitution model

The technology substitution model assembled in this chapter is the culmination of the literature and methodology arguments outlined in chapters 2, 3, and 4, the outputs of the technology classification model developed in chapter 5, and several preceding phases of model experimentation. From these studies, numerous data analysis and modelling approaches were identified, and in some cases have already been applied in chapter 5 to build the technology classification model. These included techniques based on pattern recognition, curve-fitting and correlation analysis. However, as outlined in chapter 4, these methods were not used in constructing the current technology substitution model as a fuller understanding of the causation behind patterns, behaviours, and sensitivities observed was required. In this regard, mapping the historical technology diffusion curves to a regression function in the form $y = Ax + B$ or similar may not provide a satisfactory explanation of the behaviours observed without knowing what the coefficients A and B represent (although B is conventionally assumed to be the error term or intercept). The same could be said of the ‘normalisation constants’ used in the system dynamics model below, although these terms are applied symmetrically to the weighted functional model components, and limited to specifically targeted features or interactions in the system dynamics model. The intention is to focus the uncertainty or error terms into more precise locations in the model. As such, building a system dynamics model enables causal factors to be calibrated to the empirical data, albeit possibly without the accuracy of more automated pattern recognition and regression techniques. This potentially allows more reasoning to be applied to the final model.

Other viable candidates for modelling technology adoption, as discussed in chapter 2, include bottom-up approaches such as agent-based techniques. Although bottom-up approaches have been shown to function well in a technology diffusion context, these methods were not used in the current model.

This is because the complex emergent behaviours that arise from techniques such as ABM (which may only use simple rules for the agents) make it difficult to trace and understand driving causal influences without first viewing the problem more globally. This problem extends to the validation of these models, as discussed in chapter 4. Consequently, ABM is considered as a prime-candidate to build on the work presented in this chapter, but it was felt necessary to explore different modes of substitution at a global level first before progressing to these techniques.

The earlier experimentation also highlighted features that did and did not work in the conceptual model. The first of these related to how science and technology components were combined. An earlier version of the model was built around the premise of measuring comparative differences between science and technological development efforts for an emerging technology, relative to globally observed levels of development. In this sense, the original study used bibliometric data to represent global levels of patent and academic journal publications. Metrics were then developed based on the normalised rates of progress observed in both science and technological efforts for the new technology, to gauge when science appeared to be pulling away from technology, and when technology appeared to be gaining on science. Normalisation here was based on measured global trends related to each domain. At the points where technology rapidly gained on science, a presumptive effect was assumed to occur (representing a possible 'collision'). However, when implemented in the system dynamics model, these metrics produced no distinguishable correlation to the observed adoption patterns and groups. This may have been due to significant differences observable in patent and academic journal publication trends, making relative measures between science (based on journals) and technology (based on patents) incompatible. Alternatively, this may have resulted from difficulties in trying to normalise specific technologies, from specific industries, against the same global development trends, making it impossible to devise a 'one-size-fits' all solution. As such, the current iteration focused instead solely on patent data (for traceability and consistency), and limited global measures to the accumulation of technological anomaly-related events associated with the incumbent technology. Measures of scientific and technological development efforts associated with a new technology are now normalised using a generic normalisation function, rather than against background global trends. This is elaborated further in the following sections and Appendix F.

The second conclusion from the earlier experimentation was the need to actively represent disillusionment mechanisms linked to presumptive technologies. Adoption occurred decades earlier than expected in the model without some kind of negative feedback representing potential over-hyping of these technologies or conservative responses of the market. In reality, these early adoption patterns are unlikely to take place except in times of war when needs may warrant taking larger risks on presumptive technologies (as in the development of turbojets). Consequently, the model discussed in the following sections actively represents this disillusionment feature.

6.3 Representations of scientific and technological production

Excluding technologies where counts of either the *number of non-corporates* or the *number of cited references* by priority year remained at zero throughout the emergence stage, or adoption take-off was

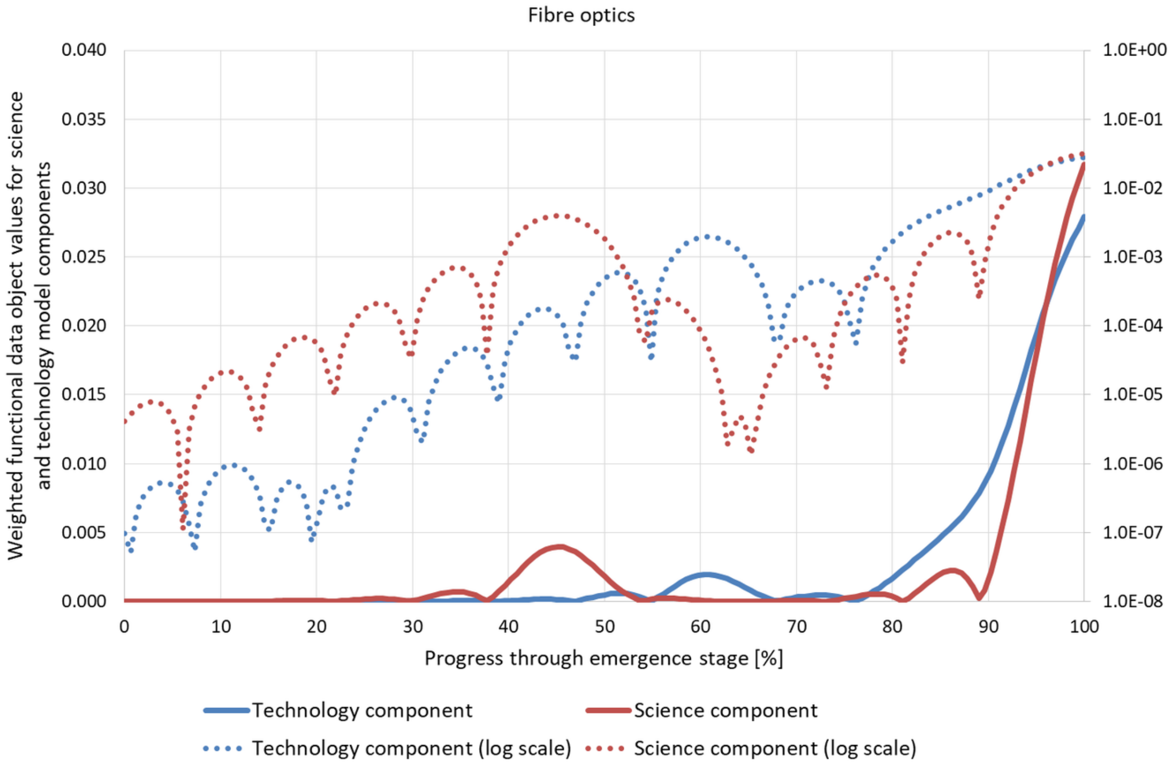


Figure 6.9: Extracted model components representing scientific and technological production in fibre optics

not captured within the collated market share data, 9 of the 20 technologies categorised in the previous chapter can be used to build and calibrate the technology substitution model. For technologies where data was not recorded during the emergence stage for these two patent indicators (assumed to represent scientific and technological development), the lack of records most likely indicates an absence of data rather than non-existence of records in the first place. This could be because these records are not available in the patent database, or were not captured by the search terms used in constructing each technology subset (although care has been taken to ensure that search strategies developed are consistent with standard bibliometric procedures, as outlined in chapters 4 and 5). Alternatively, during the emergence phase the records exist and are available, but do not originate from non-corporate assignees, include references to scientific papers, or are in a format that does not permit easy extraction of the relevant indicators without computerised character recognition algorithms. Lastly, these records may be absent if the time period corresponding to the emergence stage is not correctly bounded. Prior literature evidence has been used to try to avoid this issue, and the graphical timelines in chapter 5 appear consistent with the dates in Table 5.4. In any case, it would be inappropriate to use technologies where this crucial input data was absent in the calibration of the technology substitution model against historical diffusion curves. Equally, calibration would be heavily skewed by basing model optimisations on market share data that did not provide details of the critical take-off phase.

The unfortunate consequence of this filtering process is that only 5 reactive and 4 presumptive technologies remain for testing substitution dynamics (covering the same industries as previously, but

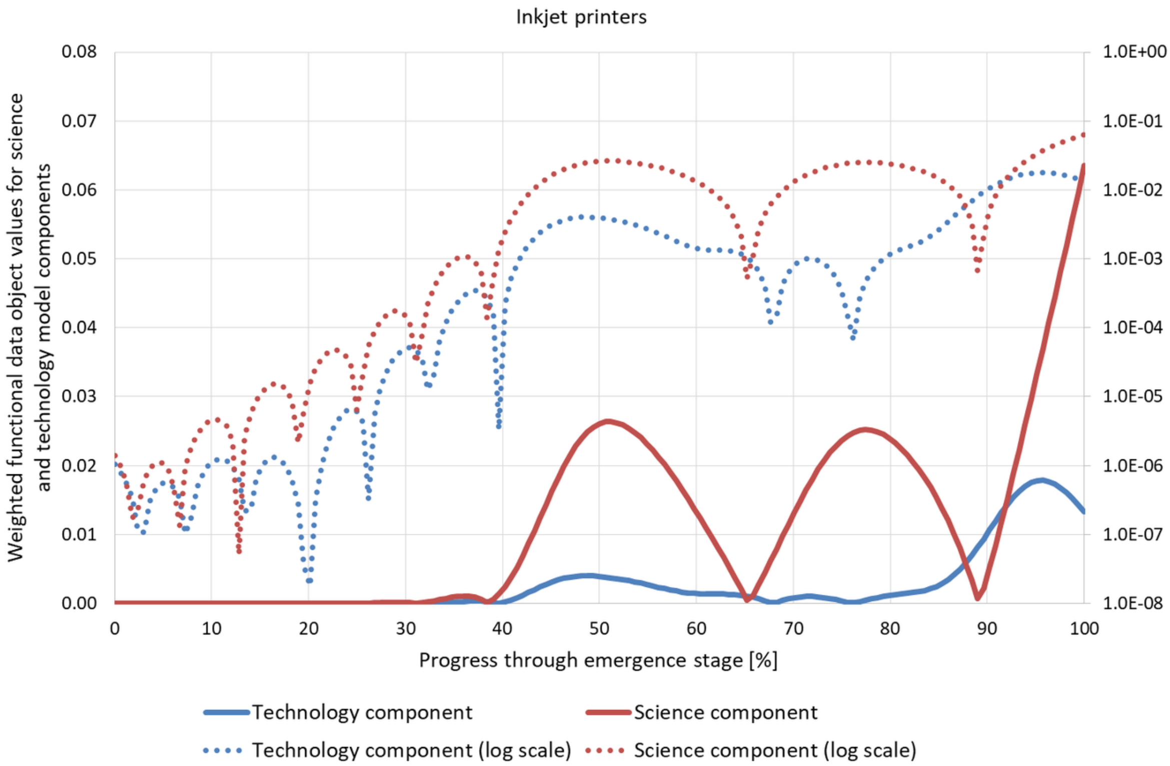


Figure 6.10: Extracted model components representing scientific and technological production in inkjet printers

with fewer examples of each). For this reason, the model, analysis, and all results in this chapter are stated as illustrative, but not definitive. The intention is to provide a demonstration of how outputs from the technology classification model in chapter 5 (i.e. weighted patent indicator functions) could guide forecasts of technology diffusion modes during the earliest conceptual stages of design, as a decision-making aid. As a first attempt, it is therefore expected that this model could be improved, supplemented by equivalent data for additional technology case studies. Nevertheless, as a decision-making tool, the ability to provide a sensible indication of trends based on causal reasoning is often sufficient to enable a good exploration of the opportunities and challenges presented by emerging technologies, without pin-point forecasting accuracy. Equally, the techniques considered here are not intended for use in isolation, and in reality would be used to compliment other decision-making aids, such as expert elicitation and industry feasibility studies.

The patent indicator counts for both the number of *non-corporate assignees* and *cited references* have been shown to enable classification of technologies by substitution mode, from data available during the emergence stage of a new technology. However, the tailored regression coefficient functions generated for these patent indicators (derived using the functional linear regression analysis in chapter 5) apply weightings to each indicator count when predicting the substitution mode for a given technology. Since the weighted versions of these patent indicator counts, here representing scientific and technological development efforts, enable technologies to be distinguished by their mode of substitution, they are assumed to be a good starting point for building a causally-linked technology

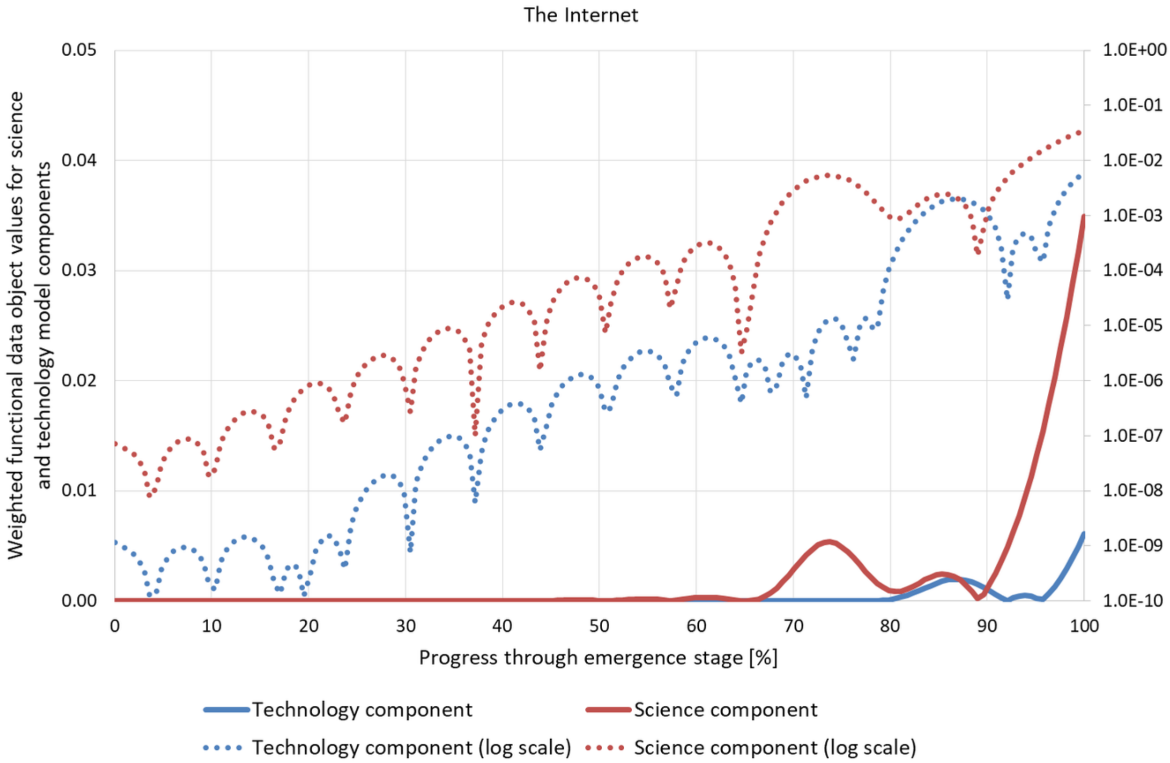


Figure 6.11: Extracted model components representing scientific and technological production for the internet

diffusion model. The weighted patent indicator counts for the remaining technologies are presented in Figs. 6.9 to 6.17, grouped into reactive and presumptive substitutions.

On first inspection, it is not immediately apparent if any common feature unites the weighted patent indicators for the reactive substitution cases shown in Figs. 6.9 to 6.13. However, when considering these indicators on a logarithmic scale (on the right-hand axis of each figure), similar patterns and features begin to appear. Firstly, although scientific development efforts tend to lead technological efforts in these examples, and be of slightly greater magnitude initially, the ramping up and stabilisation of scientific and technological development seems to be fairly closely matched. The most obvious exception to this appears for LED lights where a wider disparity between trends is observed in the first 20% of the emergence stage, and technological development efforts initially lead scientific efforts. However, the emergence trends beyond this point are mostly well-aligned. As technological efforts follow a similar, if occasionally slightly delayed, trajectory to scientific efforts, this suggests that science remains a critical driver of reactive substitutions, with technical development 'hot on its heels' in these cases. This possibly results from now recognised stagnation in the existing technology and perceived commercial need for a new product. This is potentially illustrated by the rapid introduction of multiple core microprocessors by Intel in 2006 after cooling challenges became significant to the point that a maximum practical clock rate was felt to have been reached in 2004 based on the continual miniaturisation of circuit boards and transistors [Waldrop, 2016]. Equally, in reactive cases where a new technology has recently exposed failings in the current technology (meaning that science may not have a large head start), concentrated

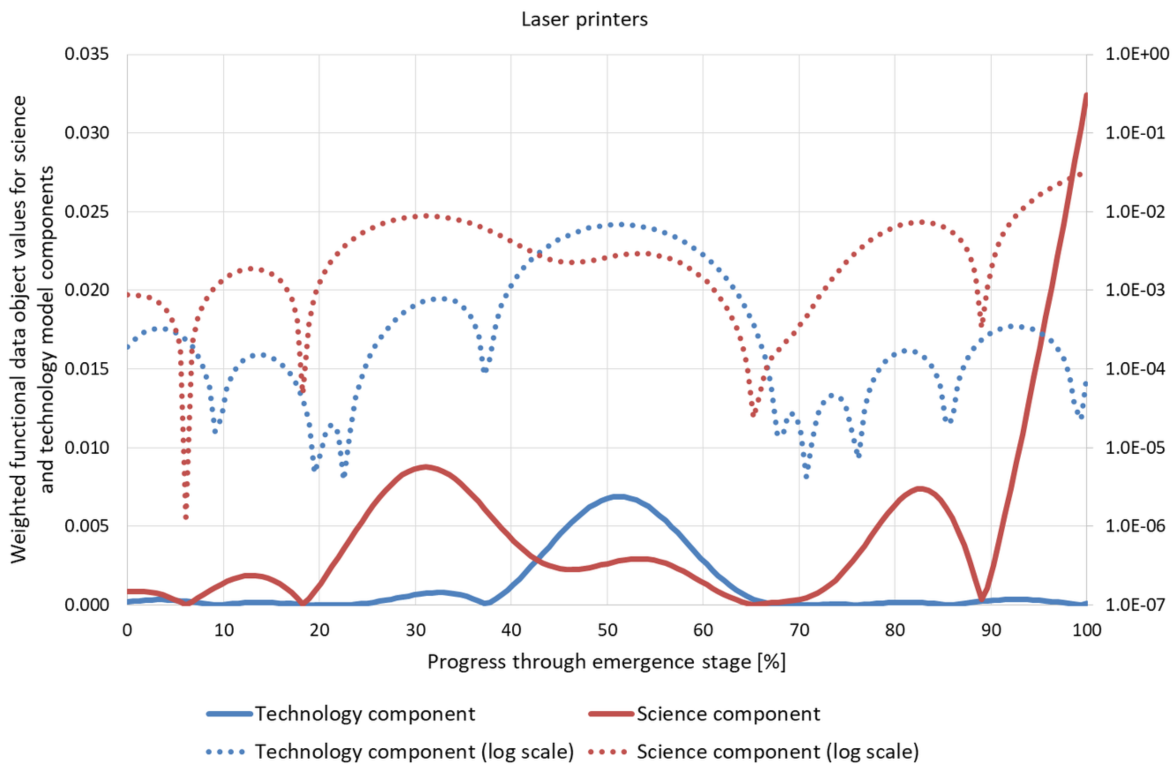


Figure 6.12: Extracted model components representing scientific and technological production in laser printers

scientific developments may follow the first patent contradicting previous assumptions, to fill gaps in existing knowledge.

The fact that there are few large surges in the *number of non-corporate assignees by priority year* for these replacement technologies could also suggest that commercialisation did not hold too many surprises in comparison to the preceding scientific development efforts. In the case of LED lights, where there is an early surge in technological development efforts relative to science, this may suggest a higher entry barrier for the new technology which was overcome when it became apparent that the preceding technology was stagnating (i.e. CFLs). This possibly coincides with the *resilience illusion* described in Adner's framework [Adner and Kapoor, 2015] where existing technologies survive based on steadily improving performance, which when first halted, presents an opportunity for new technologies to be commercialised (although this lighting transition is still in progress so this remains to be seen). In other instances, such as inkjet and laser printers, the lack of an early technological surge could imply that incumbent technologies (e.g. impact/dot matrix printers) had survived on their briefly improving performance merits, which were quickly superseded by competing technologies with relatively low emergence challenges and greater extension opportunities. These examples may correspond to the *creative destruction* quadrant described in Adner's framework [Adner and Kapoor, 2015].

The second observation that can be made from the logarithmic plots is that, with the exception of the internet, all other technologies seem to have achieved a steady level of development in both science

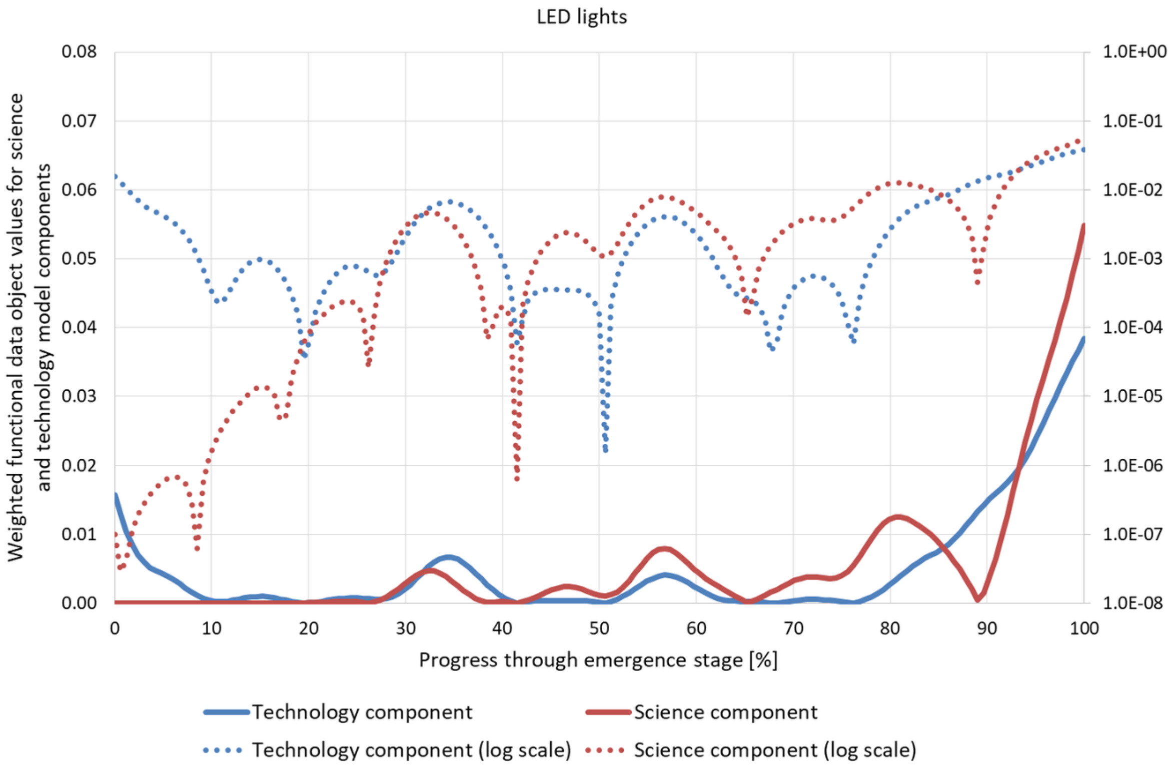


Figure 6.13: Extracted model components representing scientific and technological production in LED lights

and technology by halfway through the emergence stage (the internet appears to have reached this more mainstream development phase by about 70% of the way through the emergence phase). This perhaps reflects more serious commitments made to these technologies early in their development, driven by an existing need for a replacement. It is important to reiterate that the conjectures above are speculative, and both would need to be confirmed through examination of additional technologies due to the small sample size available for consideration here.

An additional point of note is that the short-term cyclic pattern observable in logarithmic representations of these curves (and similarly those for presumptive substitutions) occurs partly as a result of the smoothing parameter used to create the regression coefficient functions, and the use of absolute values in these figures. Absolute values are plotted rather than positive or negative values as a) it is impossible to plot logarithms of negative values, and b) this allows easier identification of patterns across both groups of technologies for the two scales used (i.e. considering just the magnitudes). Whilst these component weighting functions oscillate about zero as a reflection of each patent indicators' influence on classification at a given time, to a lesser extent (i.e. for smaller magnitude oscillations) this occurs due to the more relaxed smoothing parameter used to derive these functions. However, as noted in section 5.9.4, the smoothing parameter was selected based on the best cross-validation score. Consequently, these oscillations could be reduced further, although this may produce weightings over-fitted to the technologies in this study. This means that the coefficient

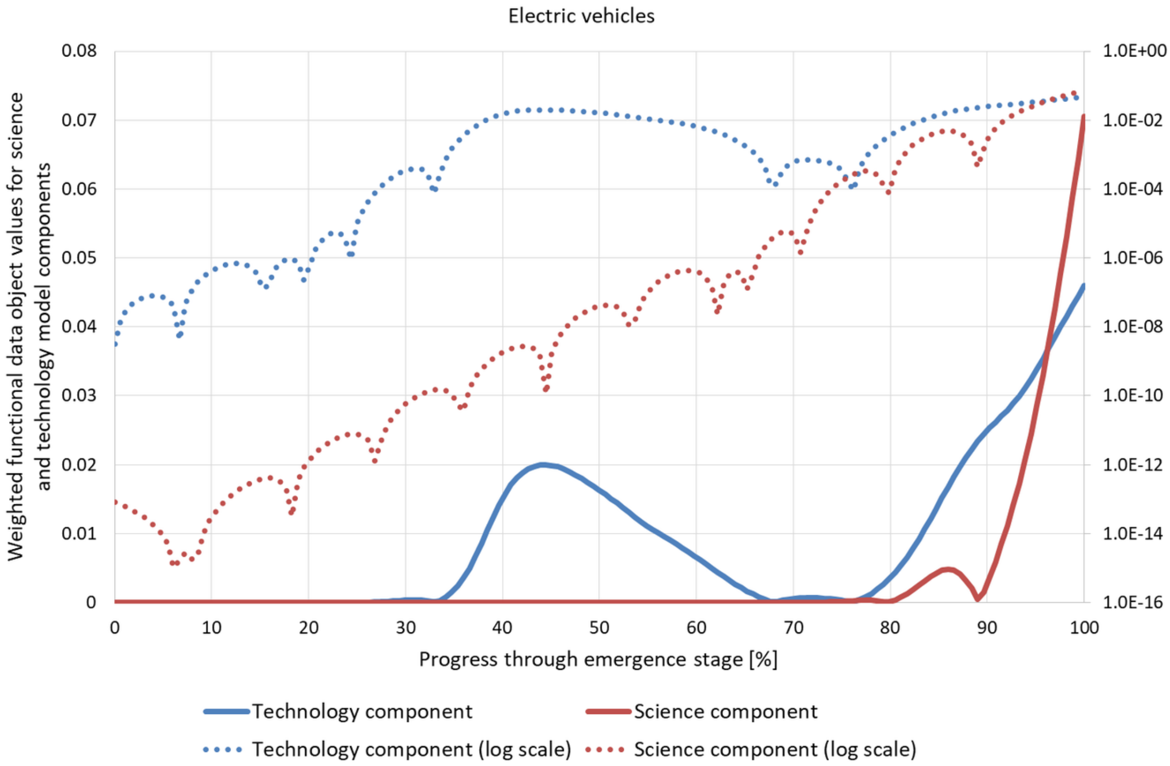


Figure 6.14: Extracted model components representing scientific and technological production in electric vehicles

functions are currently underdamped, which prevents derived functions from being overly tailored to individual technologies or industries.

In contrast to the weighted patent indicator counts illustrated for reactive substitutions, the trends shown in Figs. 6.14 to 6.17 for presumptive substitutions suggest that emergent technologies in this category experience unbalanced levels of development between science and technology. This is again most apparent when examining these trends on a logarithmic scale, however, there are some notably different conclusions.

Firstly, unlike reactive substitutions, presumptive technologies appear to undergo more extensive technological development efforts following the first identified patent, that is not matched by scientific development efforts. Whereas the weighted *cited references* trends tend to remain fairly static at low values during the first 10 to 20% of the emergence stage before steadily accelerating, the weighted *non-corporate assignees* trends suggest technological development efforts begin several orders of magnitude higher, and maintain this margin for typically 60 or 70% of the emergence stage. Following Constant's argument that presumptive technological anomalies are driven by scientific foresight [Constant, 1973], this may imply that in these conditions, core science behind the discovery is already known, potentially quite some time before the first recorded patent, and as such technology may have substantial work to do to narrow the gap relative to science. This could perhaps explain why scientific development efforts are so low initially, as new technologies may be associated with a known

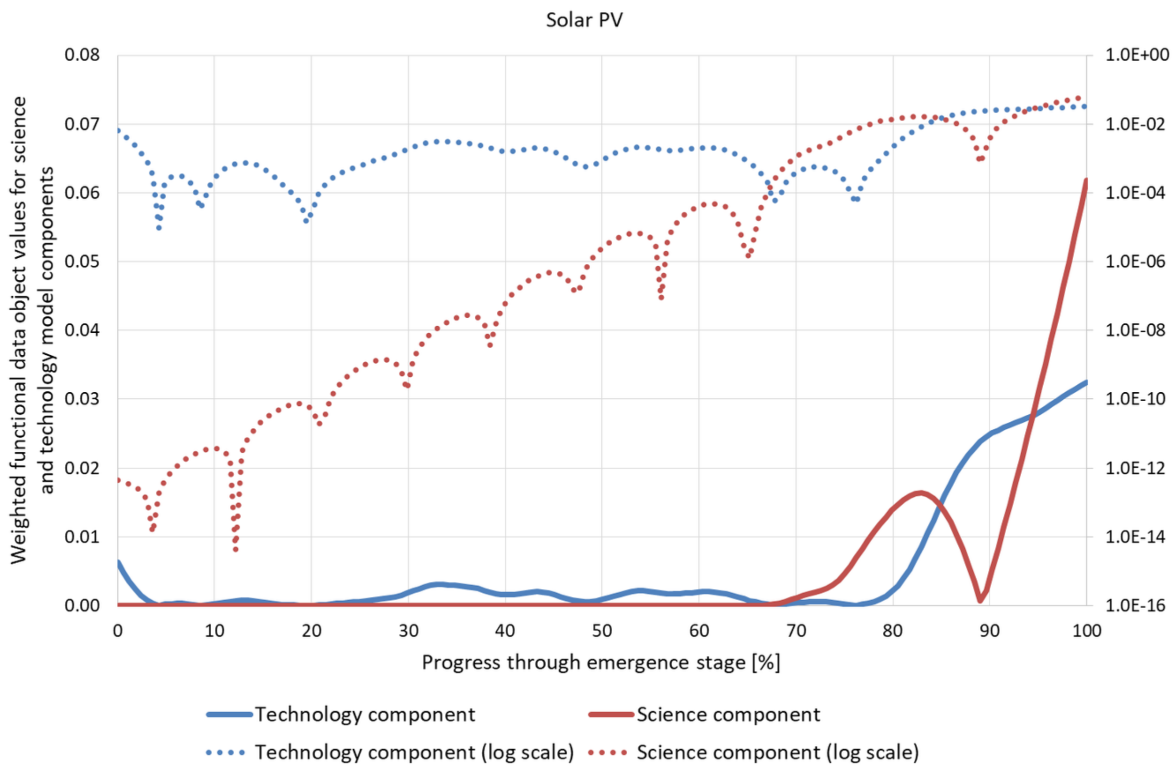


Figure 6.15: Extracted model components representing scientific and technological production in solar PV

scientific phenomenon, whilst the full technological realisation of the concept may need significantly more attention following the earliest patents.

The second feature is that despite initially sustained efforts, early activities may turn out to be a false start before technological development slows again, in a manner that perhaps reflects the hype and disillusionment cycles often linked to technology maturity [Dedehayir and Steinert, 2016, Linden and Fenn, 2003]. This is present (in some form) in all of the presumptive technologies considered (although to a lesser extent with solar PV). In each, this surge occurs before the half-way point of the emergence phase. The adoption of presumptive technologies tends to be slower than reactive technologies (observed in Fig. 6.8), which raises the prospect that the initial unbalanced surge of activity observed for the *number of non-corporates by priority year* could symbolise greater technical challenges and pitfalls in commercialising these presumptive insights. This is not an unreasonable assumption given that non-corporate assignees typically include universities, academies, non-profit laboratories and technology centres [Gao et al., 2013], which are involved in basic research and laboratory development of new technologies. Consequently, a larger number of non-corporate assignees may imply more extensive lab work to develop a technology, suggesting either an initial lack of technological maturity or considerable complexity in the technology. By contrast, technologies with fewer non-corporate assignees may be simpler and mature more rapidly. Non-corporate assignees tend to consist of a diverse spread of contributors (e.g. private inventors, citizen scientists, or small research organisations, rather than concentrated efforts from large technology organisations), so this could also suggest more

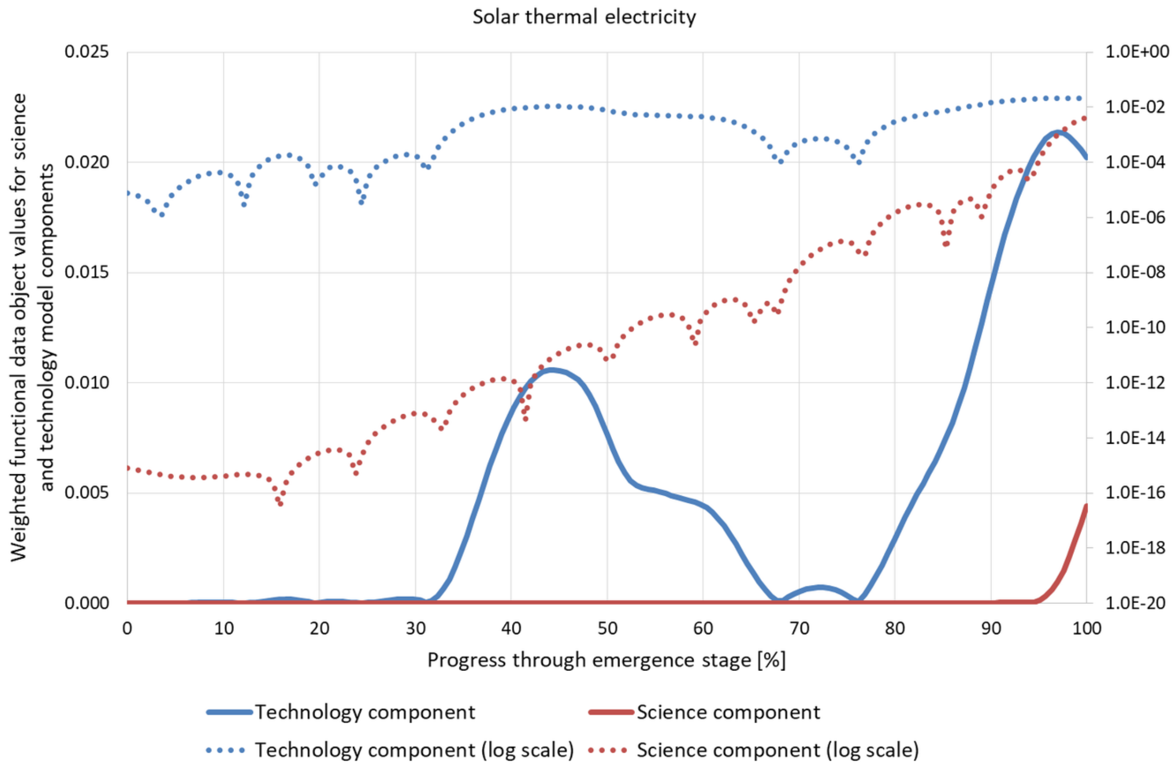


Figure 6.16: Extracted model components representing scientific and technological production in solar thermal electricity

fractured efforts to advance the technology. Increased technical efforts could therefore result from a lack of standardisation, increasingly divergent concepts that have not been narrowed down to a dominant design, or a large number of competing visions regarding the future of the nascent technology. Equally, the absence of an imminent technological failure in these circumstances may provide another explanation of why the technology component generally appears larger for presumptive rather than reactive substitutions. This may signify the extended scope of technical exploration permitted to a technology, without an immediately foreseeable commercialisation deadline. The *number of non-corporates by priority year* could therefore equate to a measure of technological complexity, or overall efforts required to mature, with larger contributions signalling a delay to adoption.

The last feature is identified by comparing scientific development terms for reactive and presumptive substitutions. From this, scientific development efforts for presumptive substitutions only appear to approach the levels observed for reactive substitutions towards the end of the emergence stage (typically 70% or more of the way through). This perhaps reflects industry's delayed commitment to build on science supporting presumptive technologies, in contrast to the pressing issues encountered in reactive conditions, where industry may be more willing to explore other scientific options for solutions at an earlier stage. Another possibility however, is that the weighted *cited references* trends do not completely reflect all scientific efforts directly attributable to a specific technology, but rather only those that were identified or deemed relevant by patent applicants. This could explain why *cited references* only appear

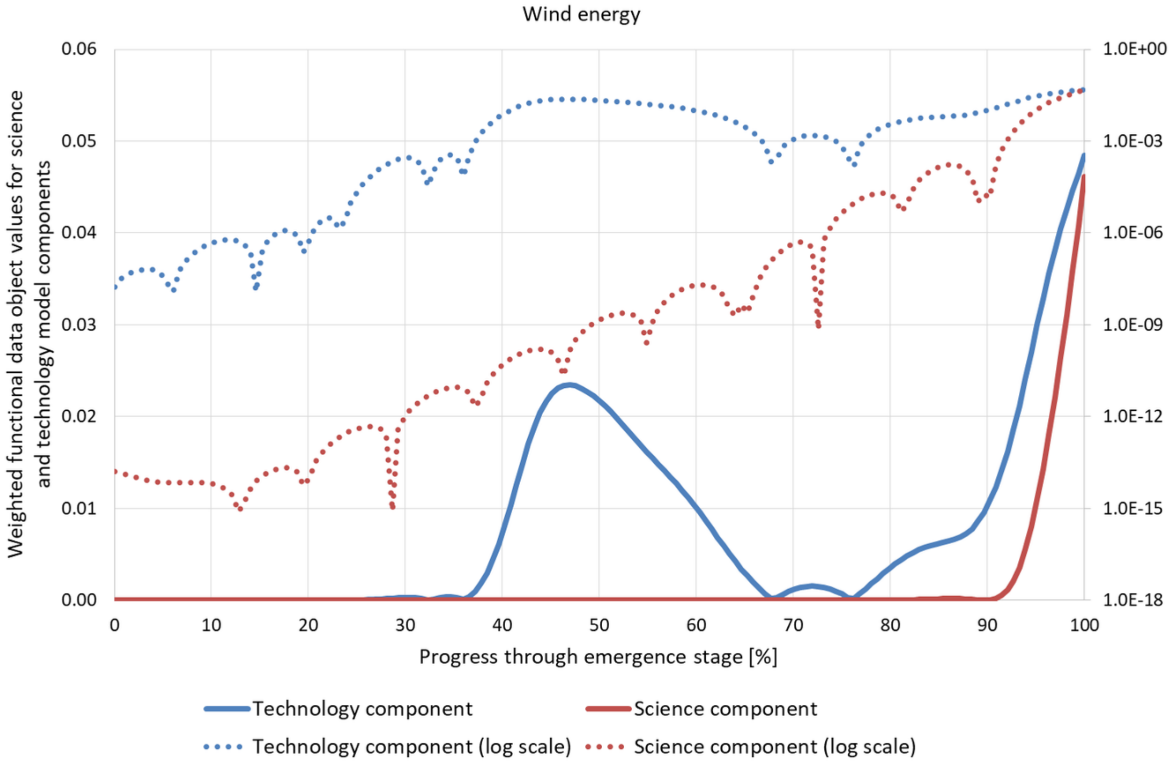


Figure 6.17: Extracted model components representing scientific and technological production in wind energy

to take-off for presumptive substitutions after substantial technological development, as it may be that at this point the technical concepts are sufficiently defined that current developments can now be referenced back to scientific articles that share a common and identifiable terminology. The consequence of this prolonged ramp up in scientific development efforts is that commercialisation and take-off in adoption of presumptive technologies often closely follows the point where scientific efforts match development levels otherwise seen in reactive technologies.

6.4 System dynamics model features and supporting logic

One of the first challenges posed when attempting to build a system dynamics model to represent a broad range of technology datasets is that life cycle durations are always dissimilar, and the length of the emergence phase proportional to the overall adoption trend changes according to technology. This is evident from the varied diffusion profiles in Fig. 6.8. Equally, take-off in adoption does not actually occur in the emergence phase itself (which corresponds to the development and first commercialisation of the new technology), but happens some time after the product is introduced to the market. However, the weighted patent indicator terms derived in the previous chapter are based solely on data pertaining to the emergence stage. This raises the question of how best to build a technology diffusion model based on emergence characteristics only, particularly when the durations of the different emergence periods change with each technology. For this reason, the first modelling assumptions are that: 1) the simulation needs to be specifically calibrated to map the data from the emergence phase against adoption trends after emergence without the use of any data from later time periods, and 2) all time periods considered must be based on a consistent relative timescale. Consequently, the model is only supplied with input values from the weighted patent indicator counts outlined in section 6.3 for the emergence phase, which are subsequently reset to zero after entering the growth phase. The model will continue to play out dynamic behaviours based on these initial inputs in the time periods that follow, meaning that presumption, adoption, and anomaly-related accumulation trends simulated are calibrated against the original data provided. As a result, calibrated values stated in this chapter are only valid when combined with data from the emergence stage. Coupling these parameter values with any later data points or life cycle stages would not produce valid outputs.

To ensure that the same relative timescale is applied throughout the model, a measure of time is used based on the number of years since the first patent in each dataset (for details of these patents, see sections 5.5.1 to 5.5.23 in chapter 5). This was chosen as opposed to the first related scientific paper or commercialisation, as this signifies the point at which an alternative technology application became apparent as a realistic candidate that could challenge the existing technology's foundations. This is the first time that any functional-failures associated with the current technology could be recognised (based on Constant's argument that technological failure is first observed when a new candidate paradigm appears [Constant, 1973]), and so it is from this point that issues associated with a technological anomaly would begin to accumulate. As discussed in section 2.2, this is distinct from the recognition of scientific anomalies, which can be observed even if there are no alternative theories available to support a new scientific paradigm [Kuhn, 1996].

As such, the year of the first patent for a technology is *year 0* for all technologies considered, with time being measured in relative year increments from this point. This means that the *INITIAL TIME* control variable in the system dynamics model should always remain as 0, whilst the *FINAL TIME* parameter is defined by the length of the longest adoption curve relative to the year of the first patent. For the technologies considered in this study, the longest adoption trends are 179 years in length (for both electric vehicles and hydroelectricity generation). As a result, in the analysis and figures that follow, the *FINAL TIME* parameter is set to 180 years. This provides the basis for the relative timescales used in later comparisons. Accordingly, the timescale is translated along the x-axis on a technology-by-technology basis, rather than attempting to stretch or compress the timescale for different technologies. In doing so, the model can easily switch between technology datasets without the risk of introducing errors (i.e. no parameter values need modifying, only array referencing subscripts). It would not make sense to shrink or stretch the emergence period to run relative to a normalised timescale (i.e. where *0* = year of first patent, and *1* = end of emergence stage), as this would require all anomaly-related accumulation rates to be adjusted for individual technologies based on the scaling factor used to distort time to fit this interval. This would make comparisons of anomaly effects between technologies complex to interpret, and in contrast to a relative timescale could also introduce both random and systemic errors into the model. The difficulty with using a relative timescale is that it adds to the preprocessing of datasets for the model, as these need to be mapped into the same time frame. This is not a problem for the regression coefficient functions derived in chapter 5, as these are already based on this time frame. However, this necessitates translation of the market share data in Figs. 6.1 to 6.7 (resulting in Fig. 6.8), and would be required if supplementing the model by any other real-world time series, such as global economic data. Once completed, it is relatively easy to use alternative 'lead-in' times as required in the simulation, by using Vensim's *DELAY* functions, which may be useful for generating background environmental dynamics prior to the date of the first patent.

Having considered consistency issues posed by segmenting different timescales, the main phenomena that the model should reproduce are addressed next. To ensure consistency with the requirements in section 2.9 for partitioning scientific and technological development influences within the derived technology classification model, it is assumed that these requirements remain true for the technology substitution model developed in this chapter. As such, the technology diffusion model needs to consider the population's awareness of a) scientific development efforts associated with the new technology, b) technological development efforts associated with the new technology, and c) the potential extension opportunities for both new and existing technologies. Presumptive substitutions then occur when perceived scientific development efforts lead to a critical mass of niche market adopters transitioning to the new technology, which has at this point in time also demonstrated basic technological applicability, enabling it to be considered as an early stage alternative. This is consistent with the description of disruptive innovation provided by Christensen [Christensen et al., 2015]. This critical mass of niche market adopters encourages wide-spread diffusion to the rest of the population, although this can be reversed if performance improvements are subsequently observed in the incumbent technology. Building on Constant's arguments of presumptive anomalies and technological substitutions discussed in section 2.2, and the framework proposed by Adner, it follows that for modelling technology adoption driven by presumption traits a), b), and c) all need to be considered for the new technology. However, recognition of either a possible future limiting condition for the existing technology or the spontaneous emergence of an alternative technology can arise from either trait a) or b) respectively, albeit without the capability at this point to influence adoption trends. For this, the model construction needs to consider the relative extension opportunities of each technology. Together, these elements enable the model to indicate if recognition of a current or future market for a replacement technology has taken place and begun to influence adoption trends (in a manner analogous to *technology push*), even if no functional-failure has yet occurred. Lastly, in the event that scientific and technological development efforts towards the new technology remain relatively muted, reactive substitutions may occur based on the accumulation of 'failure' events associated with technological anomalies (in a manner analogous to *market pull*). Consequently this feature also needs to be incorporated into the final model.

To construct a system dynamics model capable of reflecting these traits and conditions, the technology substitution model is decomposed into four constituent sub-models. These represent the influence of scientific and technological production, accumulation of events associated with technological anomalies, technology diffusion, and influence of presumption. These are discussed in the following sections (using the electric vehicles dataset as the modelled example throughout). For the construction and simulation of the system dynamics models that make up the technology substitution framework and constituent sub-models, the Vensim® simulation package is used. A summary of all the model variables, features, and supporting logic is provided in Appendix F, whilst the main calibration parameters for these models are outlined in section 6.6.

6.4.1 Model of scientific and technological production influences on confidence

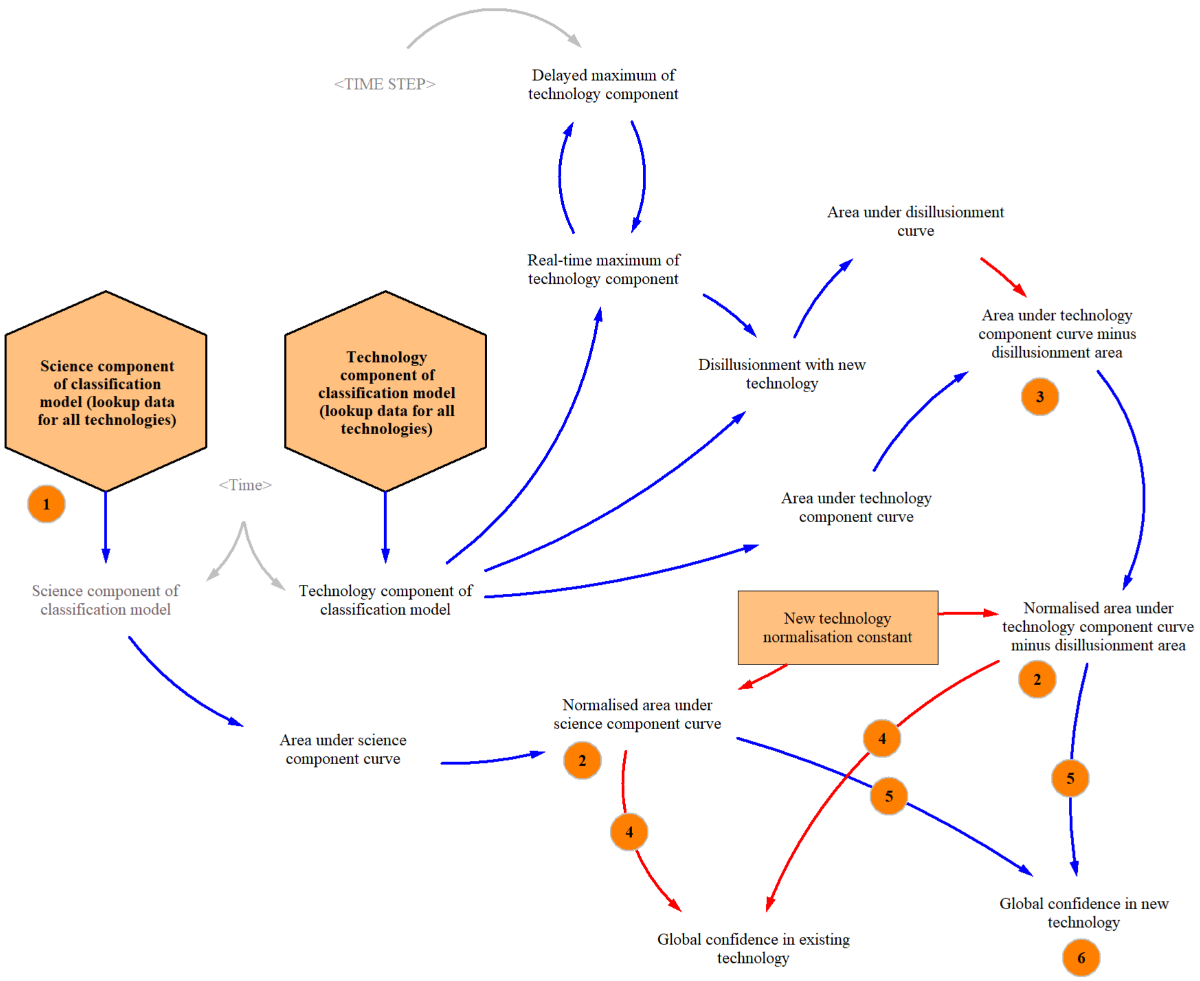


Figure 6.18: Model of scientific and technological production influences on confidence

The purpose of the first sub-model (Fig. 6.18) is to translate the representations of scientific and technological production presented in section 6.3 into estimates of the target population's confidence in both existing and emerging technologies. Consequently, the sub-model accounts for traits a) and b) by using the weighted functional data objects for *cited references* and *non-corporates by priority year* patent indicators to represent the volume of production (i.e. weighted patent counts) in science and technology respectively for the emergent technology (see chapter 5 and section 6.3 for derivation of these weighted functional data objects). The third trait, the relative extension opportunity, is measured as a binary value of either *0* or *1*, where *0* indicates that the new technology is not perceived as a realistic alternative for the existing technology, and *1* indicates a credible opportunity for improvement, based on scientific and technological development efforts recorded in traits a) and b). Specifically, the perceived extension opportunity is set to zero when either of these terms is absent (with stalled development representing a potential dead-end), and 1 when both terms are non-zero. In the fully assembled technology substitution model, the perceived extension opportunity is linked to the persuasiveness of the new technology (discussed in section 6.4.3), meaning that stunted development in either field will lead to a noticeable drop in persuasiveness for the remaining potential adopters. This accounts for the stepped pattern in some later plots of model parameters that are dependent on the *persuasiveness of new technology* variable (see Figs. 6.32, 6.34, 6.36, 6.38, 6.39, 6.43, and 6.45). Whilst this binary representation of a new technology's perceived extension opportunity is simplistic and unlikely to be realistic, it does allow the impact of this trait to be clearly traced through the model.

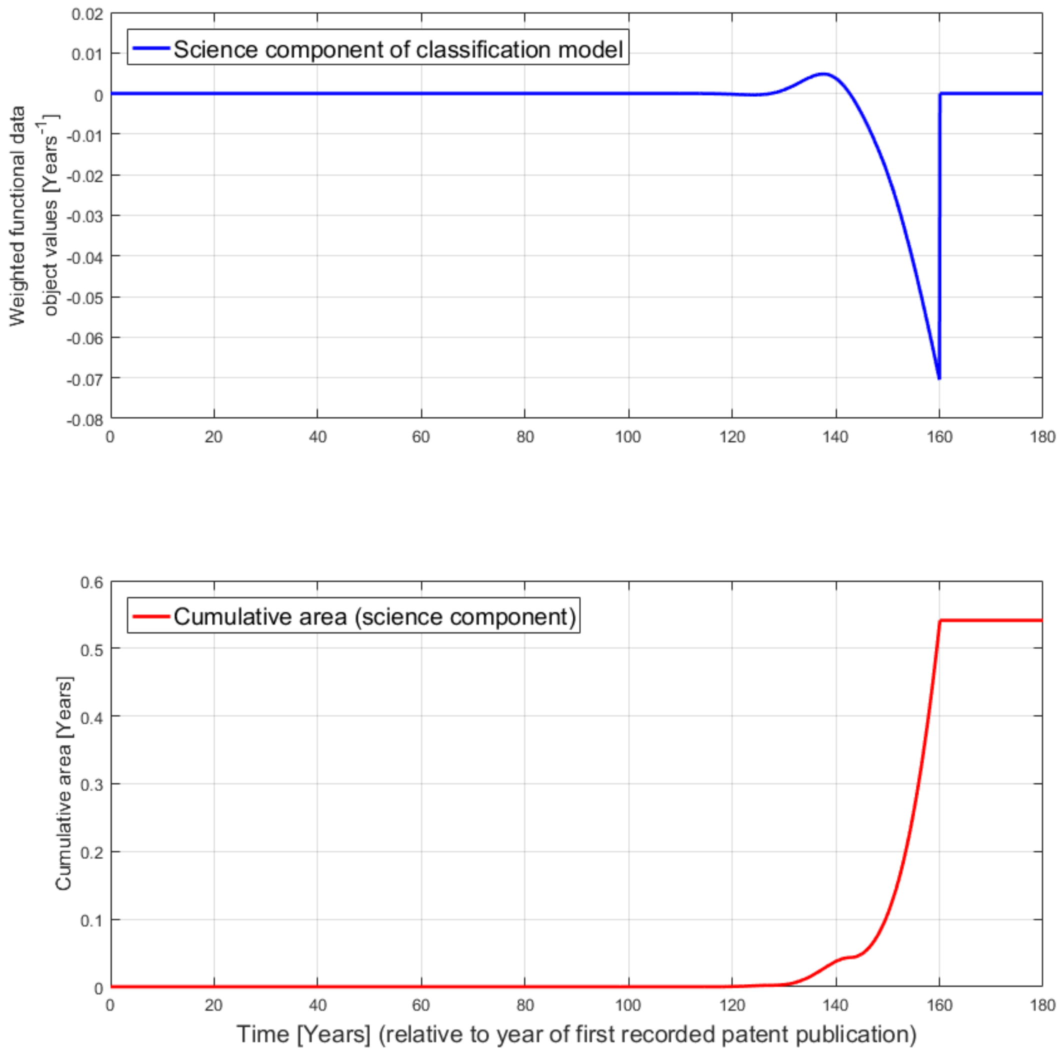


Figure 6.19: Cumulative area relating to scientific development efforts

The first feature illustrated by point 1 in Fig. 6.18 is the lookup arrays, where the weighted functional data objects representing scientific and technological production are introduced into the model. These are stored as two separate i x j x k arrays of values, where subscripts i and j correspond to the relative time and associated patent indicator count values respectively, and subscript k indicates the current technology. As discussed in section 2.6, the communication, promotion, and social impact of scientific and technological endeavours play an important role in perceptions of development, in addition to technical contributions to knowledge. Consequently, volumes of production are believed to be appropriate measures to represent a population's awareness of a new technology and its implications, rather than measures of activity or progress. By charting the volume of production for the two representative patent indicators over time, changes in perceived rates of scientific and technological development for a new technology can be tracked as they occur during emergence. The definite integral of the resulting velocity-time graphs (i.e. the cumulative area under the curves, shown in Figs. 6.19 and 6.20) is equivalent to the change in displacement during this time period, providing a distance-based measure of the relative magnitude of development efforts. This cumulative distance, recorded as years of production, shows how far the technology appears to have progressed since its inception (to an observer), and consequently plays an important role in shaping confidence levels in new and existing technologies. In addition, these trends provide a good indication of relative times of first invention and commercialisation (although, comparison with the historical case studies in chapter 5 suggests these are not always perfectly aligned). In doing so, these measures of emergence capture stages 1 and 2 of the evolution of LTS, invention and development [Hughes et al., 1987].

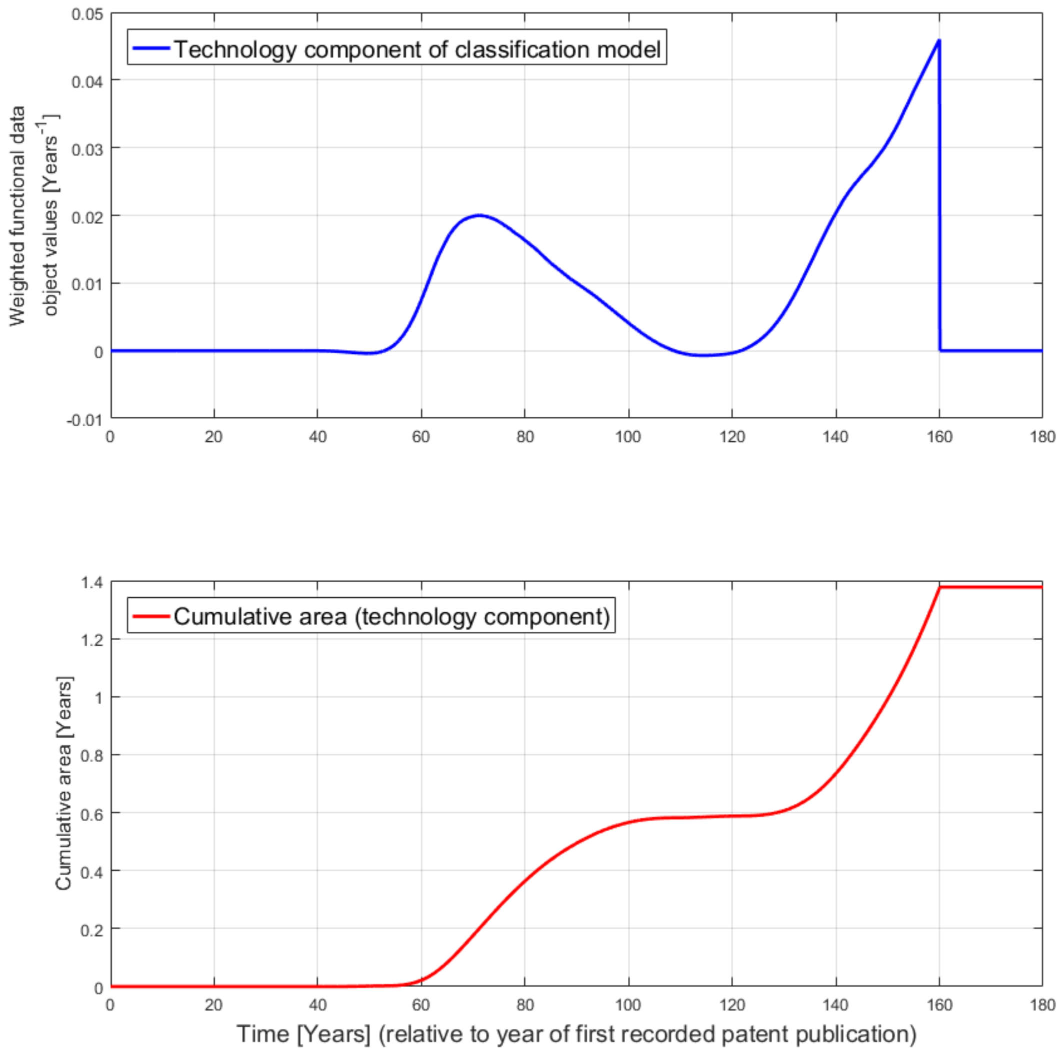


Figure 6.20: Cumulative area relating to technological development efforts

The evolving displacement measures calculated from the area enclosed by these curves, as time advances, are used to indicate perceived development efforts related to scientific and technological domains (point 2). This also hints at the extent to which the new technology is considered a mainstream development, as fringe technologies often lack the concentrated development efforts and resources required for sustained periods of growth. However, due to the possible evidence of hype and disillusionment cycles observed when considering presumptive technologies in section 6.3, and observations from earlier versions of the model, a 'disillusionment' element is specifically accounted for when deriving the displacement measure for perceived technological development efforts (point 3). Calculation of this disillusionment component, based on previously achieved development heights, is illustrated in Fig. 6.21. The technology component's running maximum is used here to measure any reduction in development efforts from their peak values. This is provided by a comparison between the technology component value at the current time step and maximum value from the previous time step. The greater of these two values is determined and stored for the next time step by the loop between the technology component's real-time and delayed maximum values in Fig. 6.18.

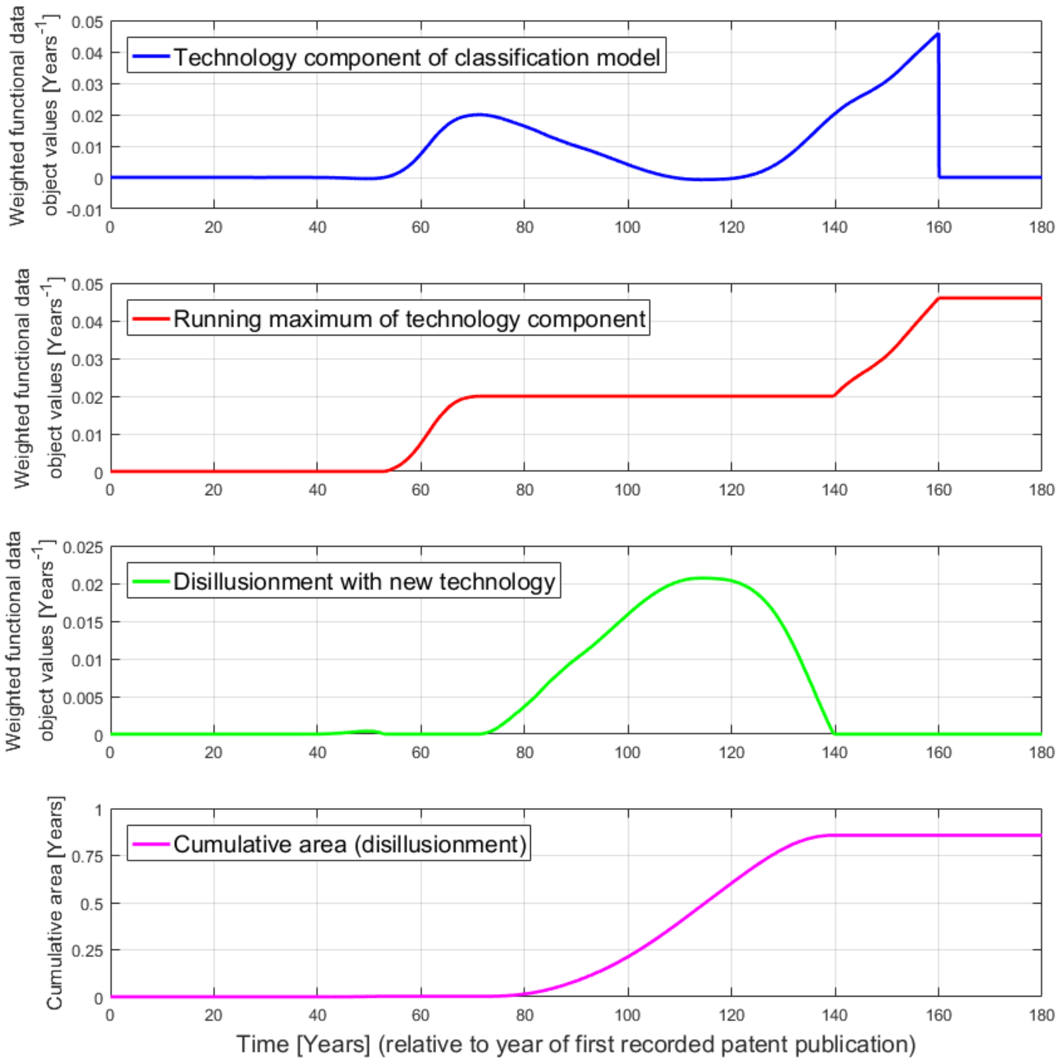


Figure 6.21: Measuring disillusionment with the new technology

Including this disillusionment term reduces the impact of the technological component in instances where an initially large surge of development subsequently tails off back to low levels, as illustrated in

Figs. 6.21 and 6.22. This accounts for how the negative hype that follows early technological and commercial failures [Dedehayir and Steinert, 2016, Linden and Fenn, 2003], coupled with greater understanding of an emerging technology's technical limitations, deflates confidence in new technologies following an initial surge in expectations. An earlier version of this model which did not include this feature resulted in technology adoption occurring decades earlier than expected for the presumptive substitutions considered. As noted in section 6.3, technology components were usually of a higher magnitude for presumptive technologies than for reactive technologies. Consequently, this resulted in a disproportionately early accelerated growth in confidence for these technologies. In reality, these early surges in confidence are unlikely to receive the necessary investment required to sustain growth at this stage, except in times of war when the risk is more likely to be deemed acceptable. This was illustrated by the accelerated development of turbomachinery during World War II.

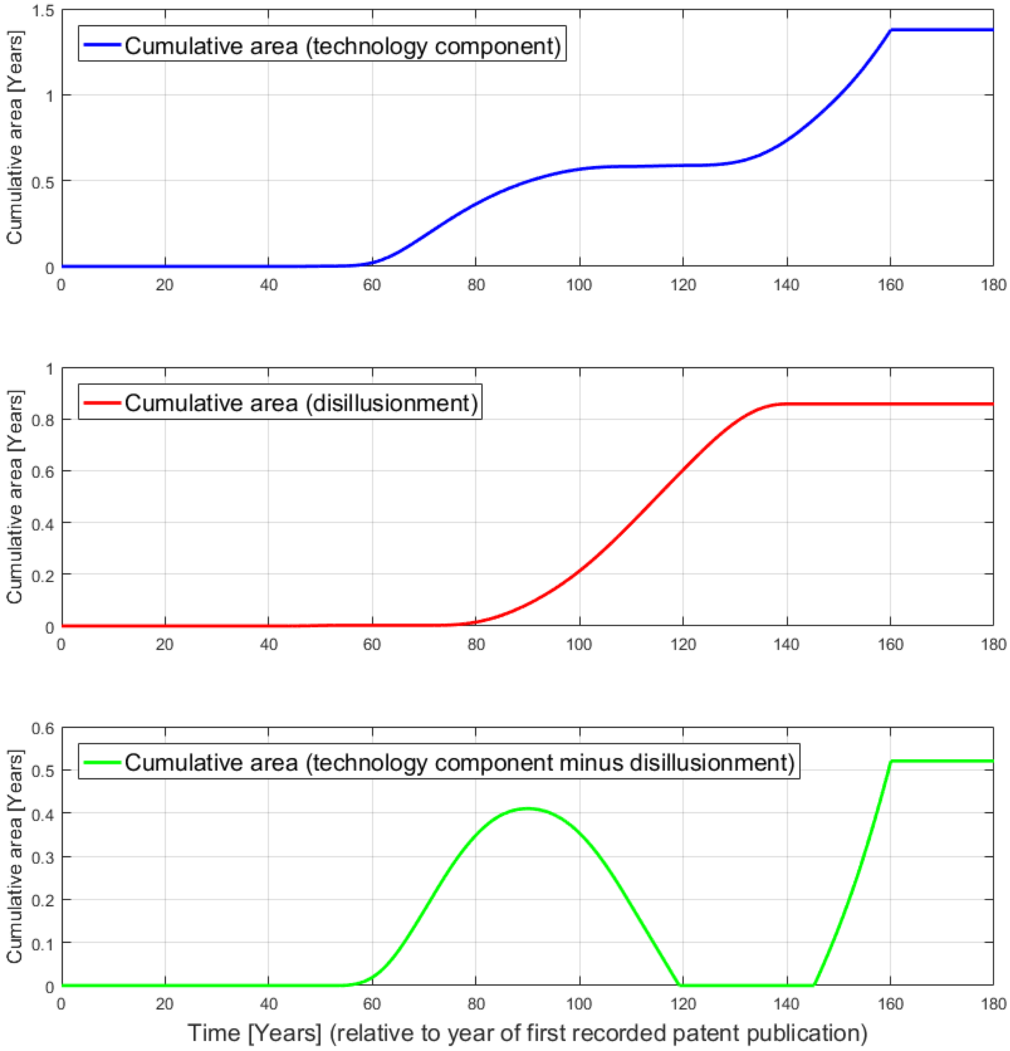


Figure 6.22: Cumulative area relating to technological development efforts, taking into account disillusionment

Any perceived increase in new technology development efforts will have different impacts on confidence levels in the incumbent and the emerging technology. For the incumbent technology, these developments pose a potential threat to its dominance, and can increase doubt and uncertainty regarding its development potential. Accordingly, confidence in the existing technology is expected to reduce, as illustrated by point 4. Conversely, early adopters are often more predisposed to rely on external influences than later adopters, with presumptive leaps made by individuals aware of scientific advances outside their native fields [Rogers et al., 2005, Dattée and Weil, 2007] (discussed further in chapter 2). Early adopters' confidence in an emerging technology is therefore likely to increase as they observe related developments, which can increase general confidence as they spread awareness in the population. This is indicated by point 5 in Fig. 6.18. Consequently, this suggests that increased production towards a new technology will have a reinforcing effect on confidence in that technology, and an opposing effect for the incumbent technology, as shown in Fig. 6.23.

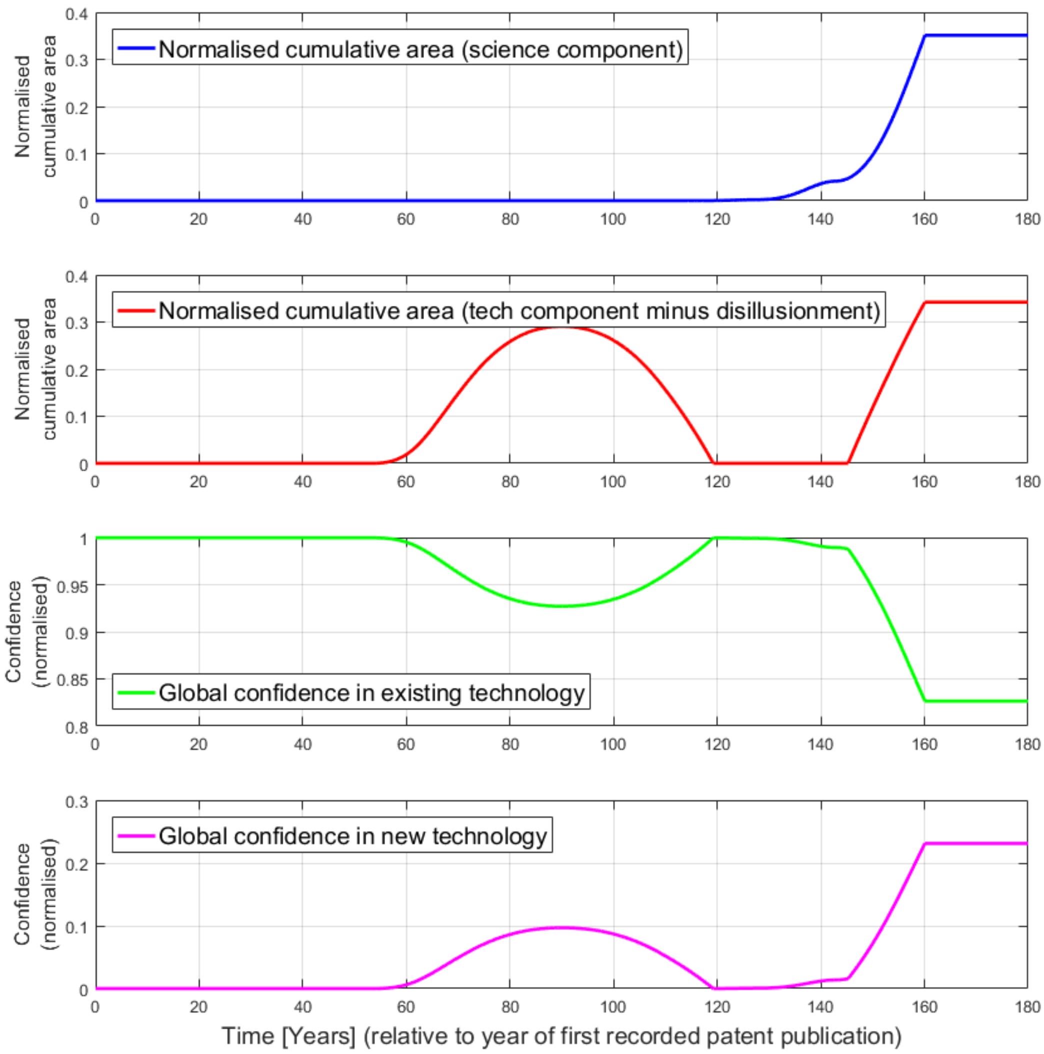


Figure 6.23: Measuring the influence of scientific and technological development efforts on global confidence in new and existing technologies

The fully assembled technology substitution model assumes that confidence in a new technology originates from the science, technical characteristics, or expertise behind it (point 6). In this regard, global confidence in a new technology is calculated from the area-based representations of scientific and technological development efforts discussed above, and the credibility of agents promoting it (discussed in section 2.7). To ensure that ‘confidence’ in a new technology is always measured on a scale of *0* to *1* (with *0* indicating no confidence and *1* indicating 100% confidence), the accumulated areas are normalised using the *new technology normalisation constant* in Table F2 (Appendix F). Fig. 6.23 illustrates how the resulting confidence measures for the existing and new technologies relate to these normalised indicators of development efforts. From this, the opposing effects on confidence, as modelled, can be seen. More specifically, developments efforts towards the new technology (including any disillusionment effects), change perceptions of obstacles to continued development, boosting confidence in it whilst undermining confidence in the existing technology. Prior to inclusion of technological anomaly and diffusion effects, this figure also shows how confidence levels calculated in the scientific and technological production sub-model directly follow the pattern of the patent development profiles. This means that if both science and technology components are zero, without any additional effects, confidence levels are either unchanged from their starting point, or returned to this. For non-zero values of scientific and technological development efforts however, confidence levels are adjusted proportionally in opposite directions. If development efforts are observed in scientific and technological fields simultaneously, a superposition effect is created that reinforces the impact of production on confidence levels for the new and existing technologies. Accordingly, parallel science and technology efforts accelerate adoption rates in the technology diffusion model compared to periods where only one of these acts in isolation.

6.4.2 Model of the influence of technological anomalies on confidence in the existing technology

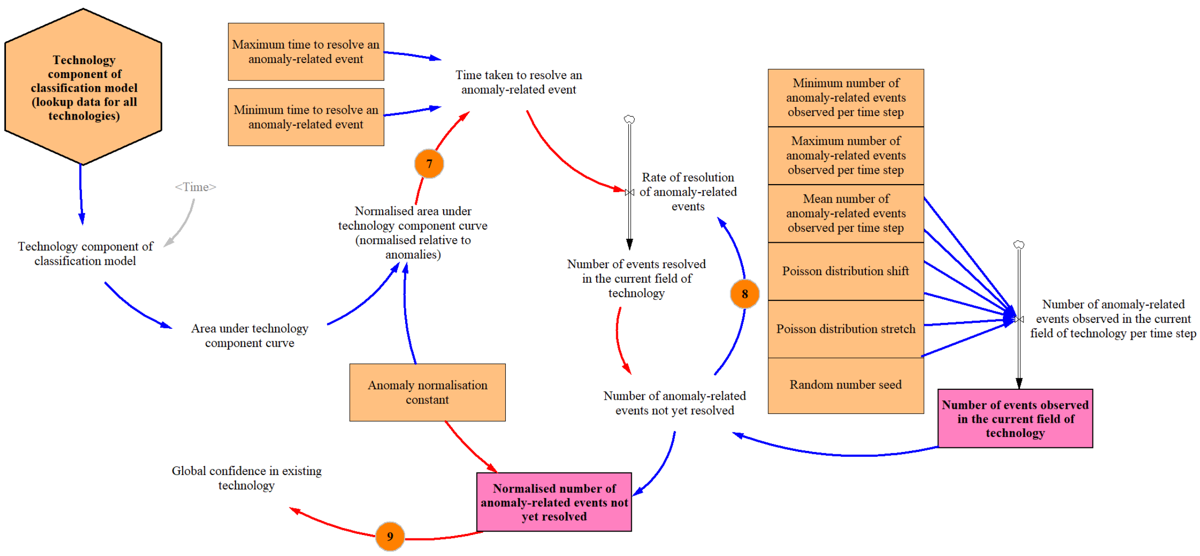


Figure 6.24: Model of the influence of technological anomalies on confidence in existing technology

The purpose of the second sub-model (Fig. 6.24) is to account for the impact of technological failure events on global confidence levels in the existing technology (direct) and the emerging technology (indirect). As discussed in chapter 2, the accumulation over time of issues linked to technological anomalies can be approximated by using a Poisson distribution to generate random failure events as the simulation advances. As a relative timescale is used in all of the models developed in this chapter, failure events can be identified from the start of each simulation (i.e. the moment that the first patent is recorded for the emergent technology), irrespective of the technology. These failure events are implemented using the Poisson distribution functionality in Vensim and the six distribution control parameters defined in Table F2 of Appendix F (grouped together in Fig. 6.24).

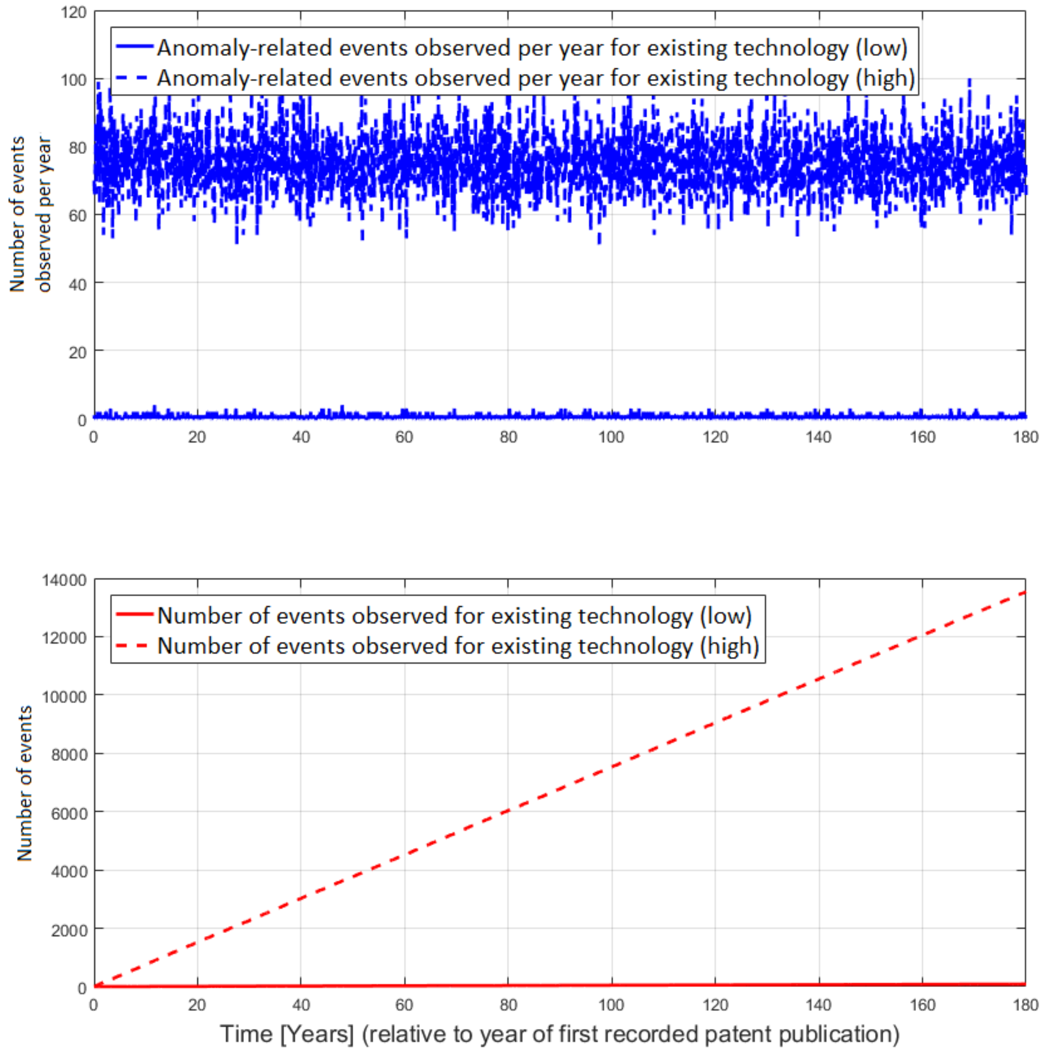


Figure 6.25: Representation of anomaly-related events based on high and low levels of event occurrence

Of these parameters, the *mean number of anomaly-related events observed per time step* is the only distribution control parameter that is actively varied in the calibration process described later, whilst the remaining distribution parameters remain at their default values. Adjusting this parameter controls the frequency of event occurrence per time step, and consequently the number of events observed, as illustrated in Fig. 6.25 for two different event frequency levels. In situations where events frequently occur, the global awareness, and consequently significance, of the related anomaly is assumed to increase more rapidly.

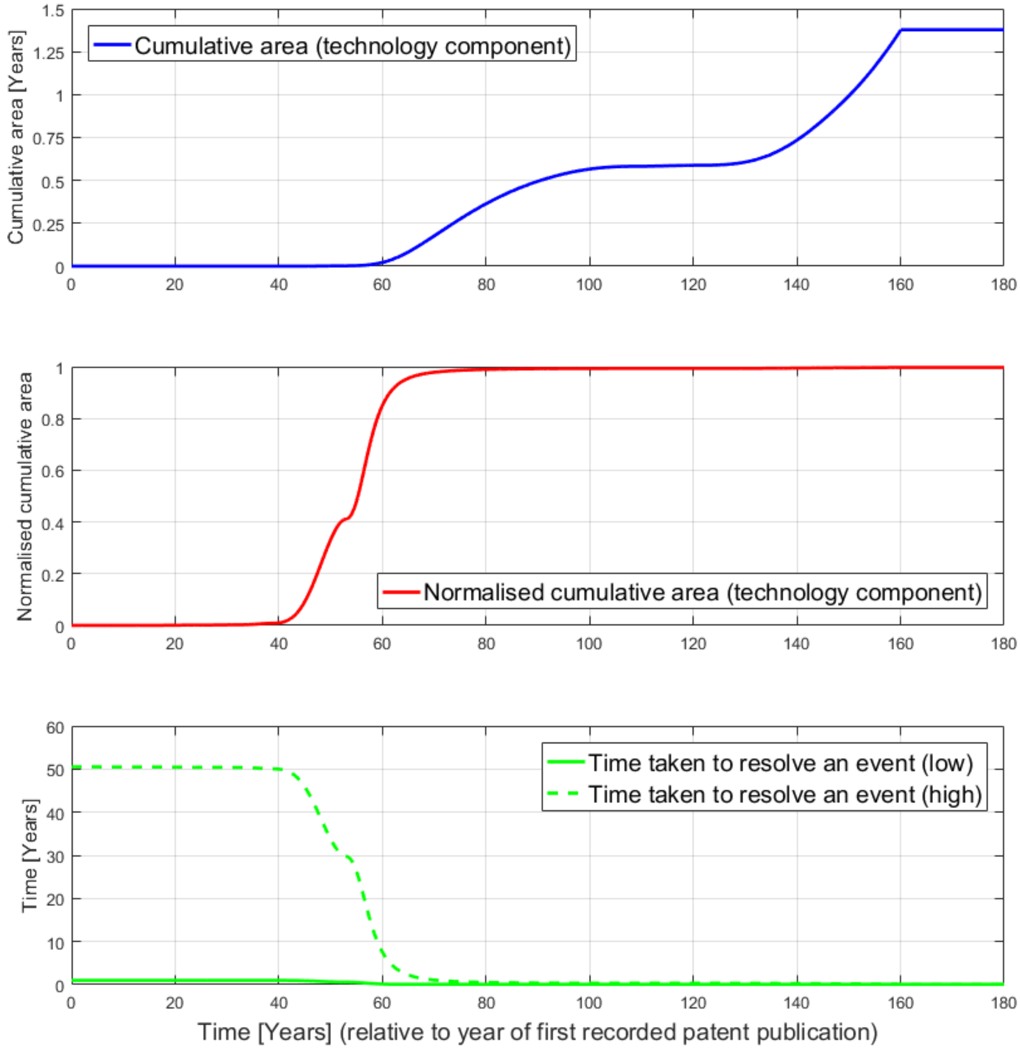


Figure 6.26: Influence of competing technological development efforts on the time taken to resolve anomaly-related events under high and low stagnation initial conditions

In this sub-model, the failure events generated by the Poisson distribution increase the total number of unresolved issues. However, in parallel to the on-going detection of anomaly-related events, this sub-model also simulates attempts to resolve outstanding anomaly-related issues. This is based on the maximum and minimum times required to resolve an issue, and a representation of observed technological developments for the competing emergent technology. Event resolution times vary within these bounds subject to Constant's conjecture that technological failure first becomes apparent when a new candidate paradigm appears [Constant, 1973]). As such, prior to this point, the time to resolve issues associated with technological anomalies is assumed to rest at its maximum value. At this time, association with anomalies is rejected by scientific and technological communities [Kuhn, 1996]. In the meantime, technological challenges posed by anomalies may be resolved as a course of routine development of the incumbent technology, but may not be recognised as symptomatic of an anomaly. Once the competing technology becomes more visible, the technological shortcomings are assumed to be more proactively addressed, leading to a reduction in the time taken to resolve issues relative to the original maximum (point 7 in Fig. 6.24). This effect can be more or less pronounced, depending on the initial time taken to resolve each issue (assumed to correspond to the level of stagnation in the existing technology before any re-energisation takes place), as illustrated in Fig. 6.26.

Anomaly-related events are assumed to be resolved at a rate that increases proportionally to the number of unresolved events, and inversely proportional to the time taken to resolve each event (see Fig. 6.27). This is based on the tendency of vested industries to resist moves away from the currently dominant technology, responding instead by increasing efforts to resolve known obstacles to further performance improvements, often referred to as the 'sailing ship' effect (point 8) [Constant, 1973, Kuhn, 1996, Ward, 1967]. The impact of these reinvigorated efforts on the number of resolved and as yet unresolved events for the existing technology is modelled in Figs. 6.27 and 6.28 respectively, under high and low event accumulation conditions.

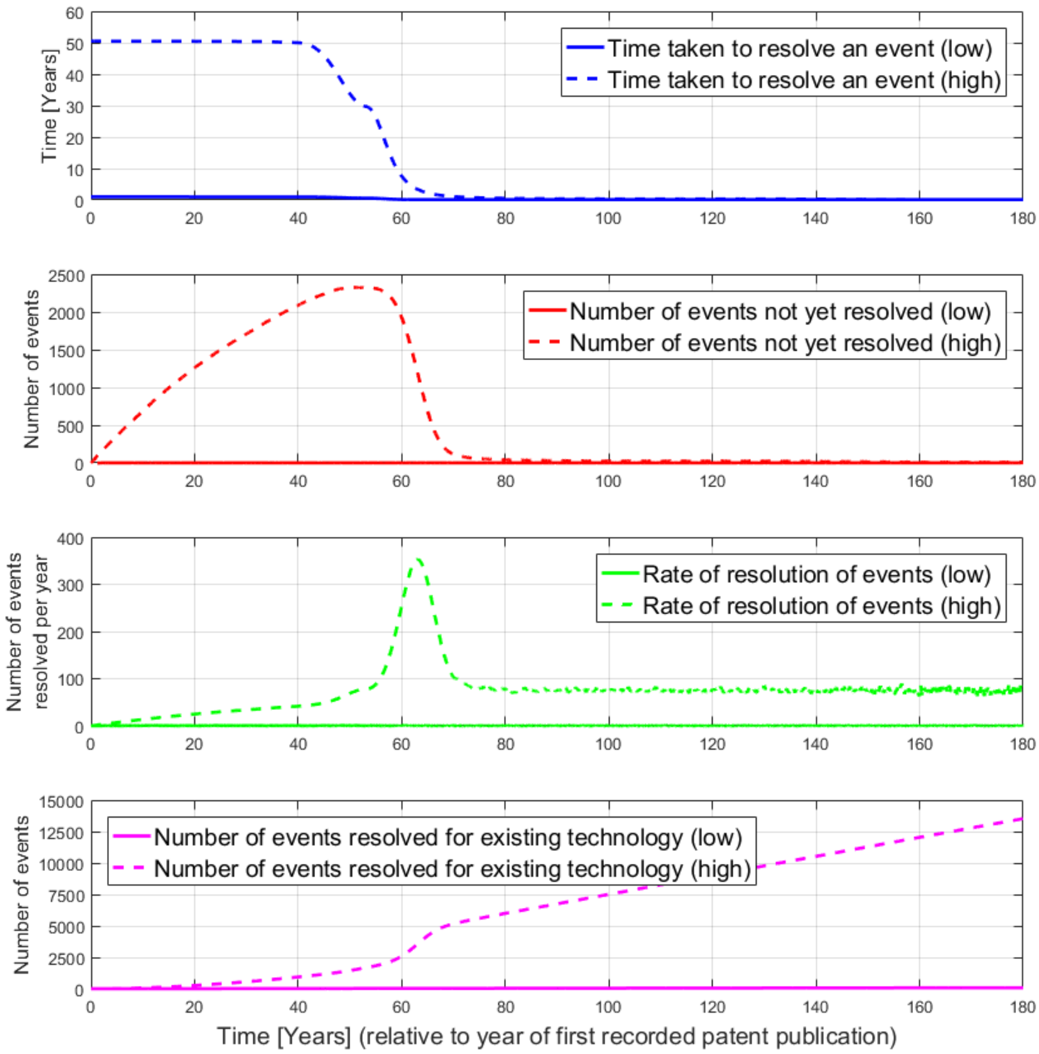


Figure 6.27: Influence of the initial time taken to resolve anomaly-related events on the accumulation of events and rate of resolution

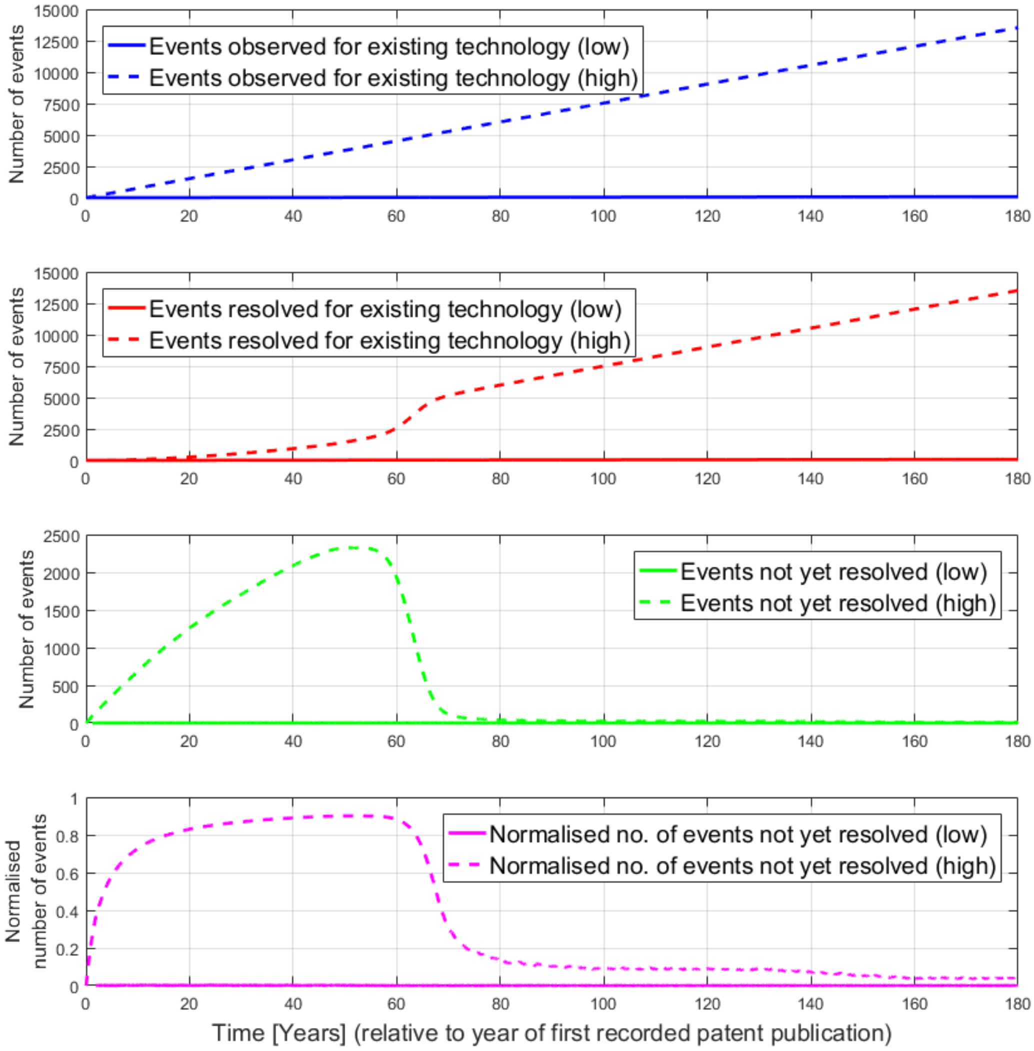


Figure 6.28: The influence of high and low event accumulation on the number of unresolved events

In reality, industrial efforts to continue developing an existing technology usually subside when it becomes clear that the challenges faced by it are far outweighed by the opportunities presented by the new technology. In the model, accumulation of anomaly-related events indicates a steadily increasing backlog of challenges associated with an incumbent technology. In these conditions, an emergent technology from a niche market sector that is on a steeper performance improvement trajectory would provide an appealing alternative to the incumbent technology, encouraging a shift in development efforts [Christensen et al., 2015]. However, in the current representation of technological failure, the reduction in efforts for the old technology once it has been displaced is not included. This is because, from the evidence in chapter 2, incumbent technologies can improve to a point where they overtake emergent technologies once again. Examples of this include the reappearance of steel as a construction material for car bodies, and reintroduction of advanced aluminium alloys as a structural material for aircraft components. Resurgence of previous technological paradigms can therefore occur, making two-way substitutions possible. However, for the purposes of this model, the formulation maximises the delay to new technology diffusion (accounting for any 'sailing ship' effects) whilst eliminating uncertainty associated with trying to identify a point of resurgence. Consequently, the model is thought to be suitable for representing an initial substitution, but not for any ensuing substitutions resulting from reinvigorated development efforts. More complex model configurations could be proposed to represent alternate reactions from incumbent industries, by either reducing the rate of issue resolution once a new dominant technology is established (i.e. resuming the accumulation of anomaly-related events for the existing technology), or reversing adoption trends based on the reinvigorated performance of the existing technology. This may enable a closer representation of the four lower level substitution modes outlined in Adner's framework by specifically considering scenarios of *creative destruction*, *robust coexistence*, *resilience illusion*, and *robust resilience* [Adner and Kapoor, 2015]. However, for the current examination of the two higher modes of substitution, the present model is considered reasonable, in which the accumulation of anomaly-related events creates a tipping point where substitution to the new technology occurs.

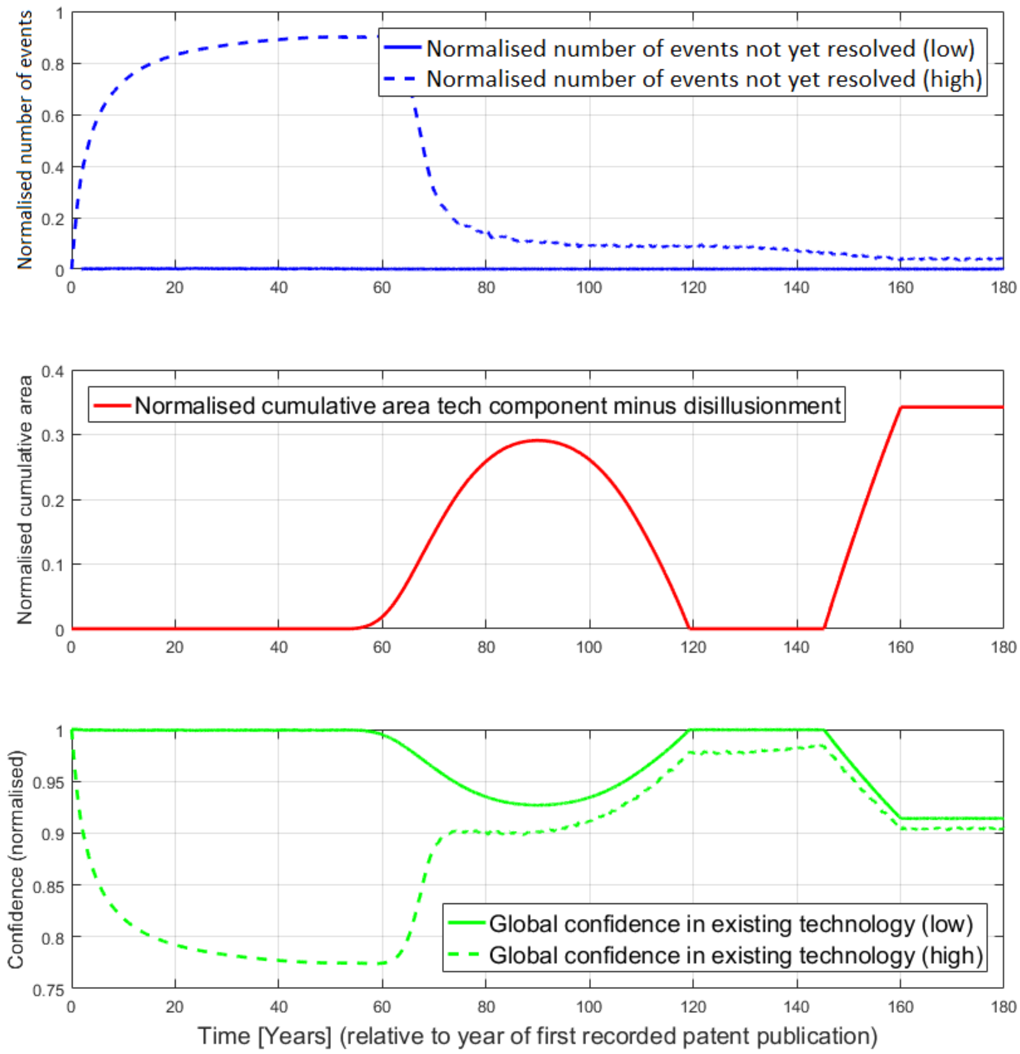


Figure 6.29: Influence of high and low event accumulation on global confidence in the existing technology

As mentioned previously, the technology substitution model treats the continual accumulation of anomaly-related events as an indicator of technological failure. However, in cases where technological issues are successfully resolved, the events can be considered as newly classified discoveries or inventions. Consequently, the rate of resolution of events/issues can be regarded as a relative measure of inventiveness associated with the existing technology, driven by the development of the new technology. Therefore the technological anomaly sub-model partially accounts for *invention* and *competition* (1st and 6th stages of LTS evolution described by Hughes), by capturing the increased inventiveness of incumbent industries responding to growth in new technologies [Hughes et al., 1987]. This is only partial as competition effects are limited to those arising in a single incumbent and emerging technology pair, with invention represented indirectly for the emerging technology relative to the existing technology. Invention of the new technology is primarily captured through the weighted bibliometric profiles introduced in the scientific and technological production sub-model (see section 6.4.1). However, increased inventiveness in response to competing development efforts (modelled as a reduction in the normalised number of unresolved issues) is assumed to reinstate confidence in the existing technology (see Fig. 6.29), slowing further adoption of the new technology.

By contrast, Fig. 6.29 shows that the accumulation of a large number of anomaly-related events creates a lack of confidence considerably earlier in the development of the new technology, which could lead to a substitution tipping point that would not otherwise have taken place at that stage. This is because in this condition, unresolved issues with the existing technology (representing reverse salients) can undermine fundamental assumptions of future projections, and therefore outlook for continued market dominance [Hughes et al., 1987]. The high event accumulation scenario is not represented realistically here, because if confidence in the existing technology had reduced significantly due to numerous issues early in the new technology's life cycle, then it is likely that development efforts towards the new technology would have increased substantially in response. This means that the 'hype' bubble that is subsequently followed by renewed interest (which both happened later in the emergence stage when considering electric vehicles), would be more likely to overlap with the earlier dip in confidence from the accumulation of anomaly-related events. However, this example shows a forced simulation condition to illustrate the two extremes, and is not therefore representative of actual behaviour recorded for electric vehicles in this scenario. Hypothetically, if an accumulation of issues on this scale had been observed for petrol and diesel vehicles then Fig. 6.29 illustrates how vested industries' confidence in continued development may have been shaken at an earlier point in time. In this case, electric vehicles may not have emerged as a presumptive substitution, but rather as a reaction to the declining fortunes of petrol and diesel. For example, this would have been true if electric vehicles had re-emerged due to recent legislation aiming to phase-out diesel vehicle sales by 2040 (following the VW emissions scandal of 2015), but in reality electric vehicles reappeared prior to this point. When event accumulation takes place at a very low level, confidence in the existing technology is otherwise driven by developments observed in the emerging technology (matching the confidence trend seen previously in Fig. 6.23). The contrasting profiles expected for global confidence in the existing technology under these two extremes makes Fig. 6.29 a useful depiction of the distinctive behaviours expected for reactive and presumptive substitutions.

6.4.3 Technology diffusion model

The purpose of the third sub-model (Fig. 6.30) is to account for the diffusion of the emergent technology through the population, based on the confidence in the two competing technologies when considering the internal and external influences on adopter behaviours. From the discussion of technology diffusion research in chapter 2, the well-established Bass diffusion model is used here to construct the core elements of this sub-model, assuming the classic technology adoption profile described by Rogers (point 10 in Fig. 6.30) [Bass, 1969, Rogers, 2010, Rogers et al., 2005].

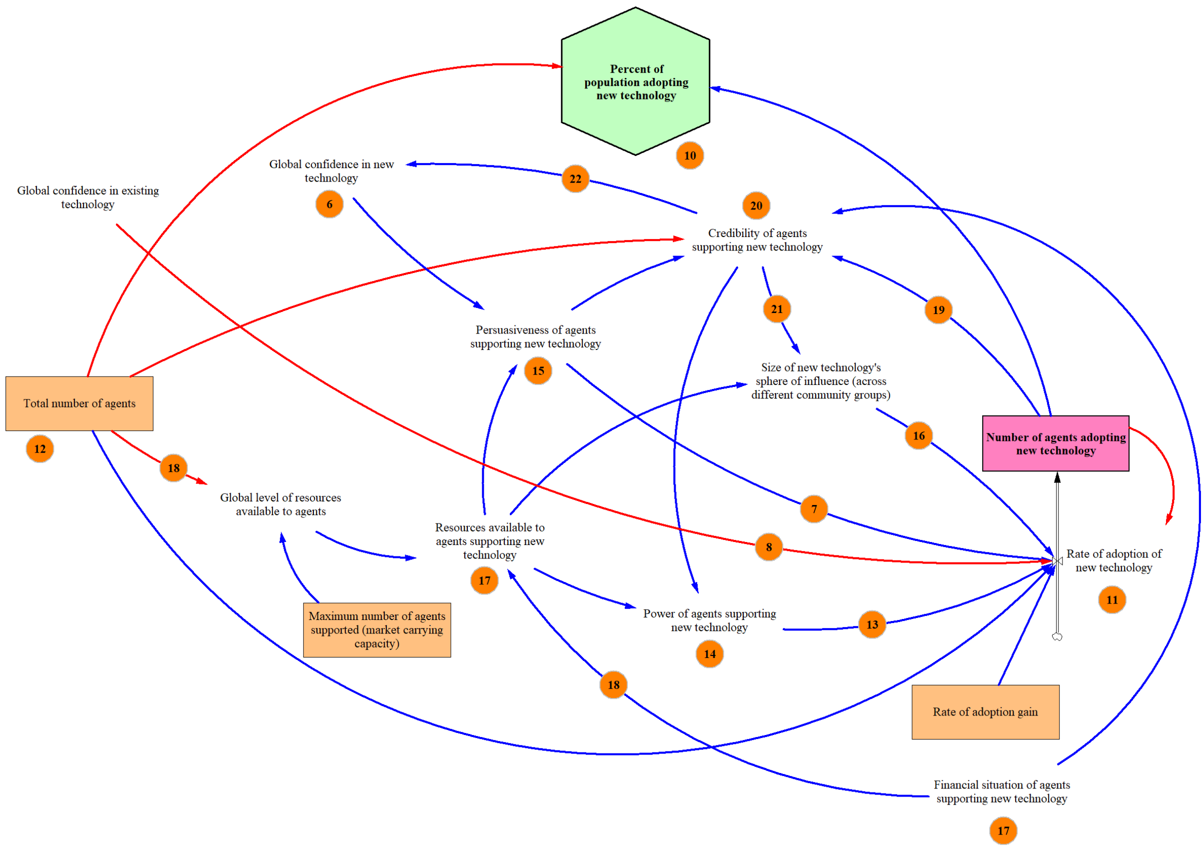


Figure 6.30: Technology diffusion model taking into account the level of confidence in both new and existing technologies

As is customary for the Bass diffusion model, influences from marketing effects (i.e. external influences, known as the *coefficient of innovation*) and social interactions (i.e. internal influences, known as the *coefficient of imitation*) correspond to the p and q terms respectively in the calculation of the rate of adoption (see chapter 2 for further details). The formulation ensures that the rate of adoption greatly accelerates once a critical mass of adopters is achieved (akin to 'Little's Wall' [Constant, 1973, Rogers et al., 2005]), beyond which the rate of adoption is no longer linear, or locally restricted (point 11). An adoption fraction is then calculated as a ratio of the number of adopters to the overall population size. Based on the findings of Goldenberg et al., the population size in the following studies is set to 1,000 agents unless otherwise stated (point 12) [Goldenberg et al., 2001].

Considering external influences first, the technology diffusion sub-model uses a combination of three parameters to represent the *coefficient of innovation*: the *power of new technology advocates* [Bass, 1969, 2004, Constant, 1973, Harty, 2005, Lunenburg, 2012, French et al., 1959], *persuasiveness of the new technology* (taking into account its perceived extension opportunity) [Rogers, 2010], and *size of the new technology's sphere of influence* [Lunenburg, 2012, Harty, 2005]. Having a large power base (i.e. strong backing) has been shown to accelerate the rate of adoption (point 13) [Constant, 1973, Bass, 1969, 2004]. Consequently in this model, *power of new technology advocates* represents the ability of advocates to control potential adopters' willingness to switch to the emergent technology, resulting from an advocate's control of resources and their own expertise (in this case represented by their credibility), as shown in Fig. 6.31 and Fig. 6.32 (point 14). This uses a simplified version of French and Raven's framework on the sources of power [French et al., 1959].

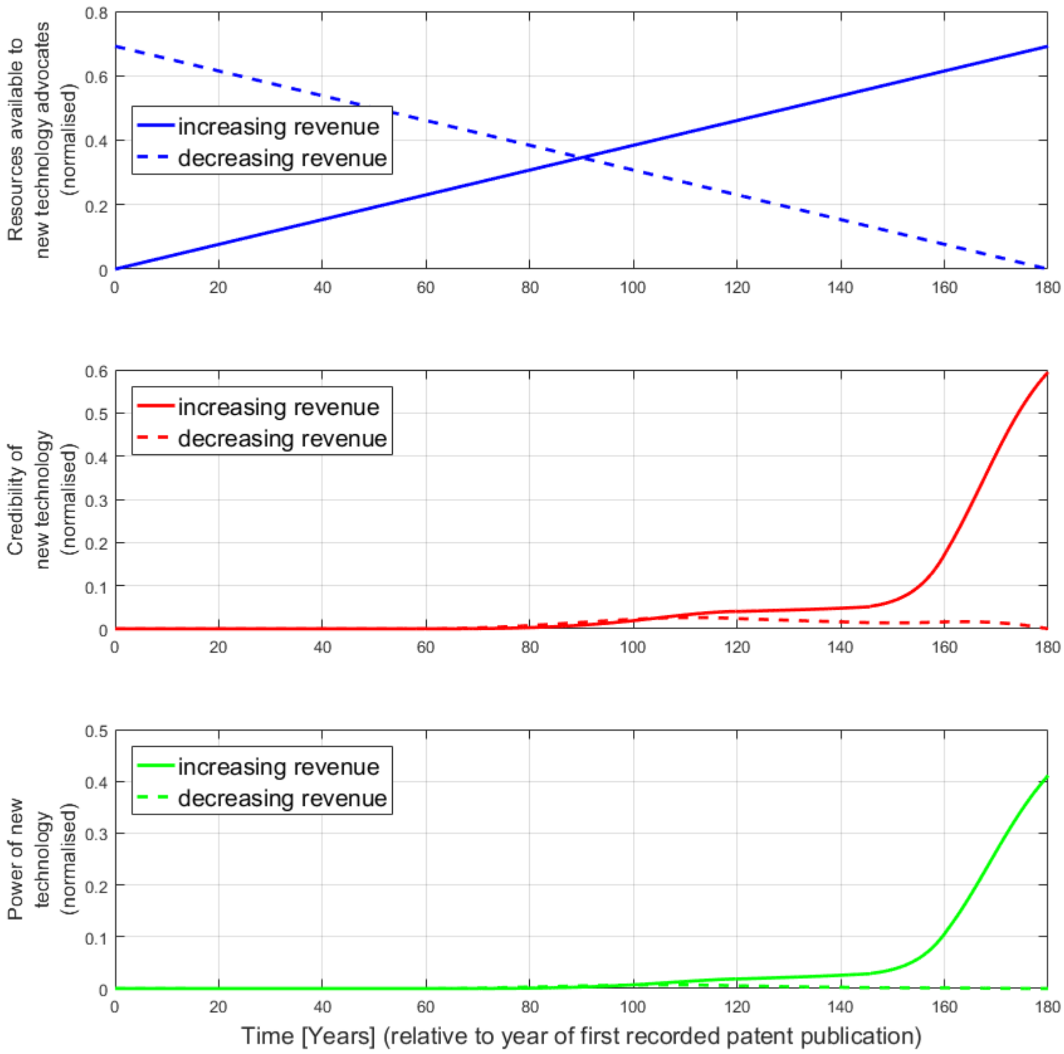


Figure 6.31: Influence of varying revenue generation scenarios on the power of new technology advocates

In this study, *persuasiveness of the new technology* indicates the strength of the argument for change, put forward by its advocates. Arguments are assumed to be persuasive if there is rationale behind the

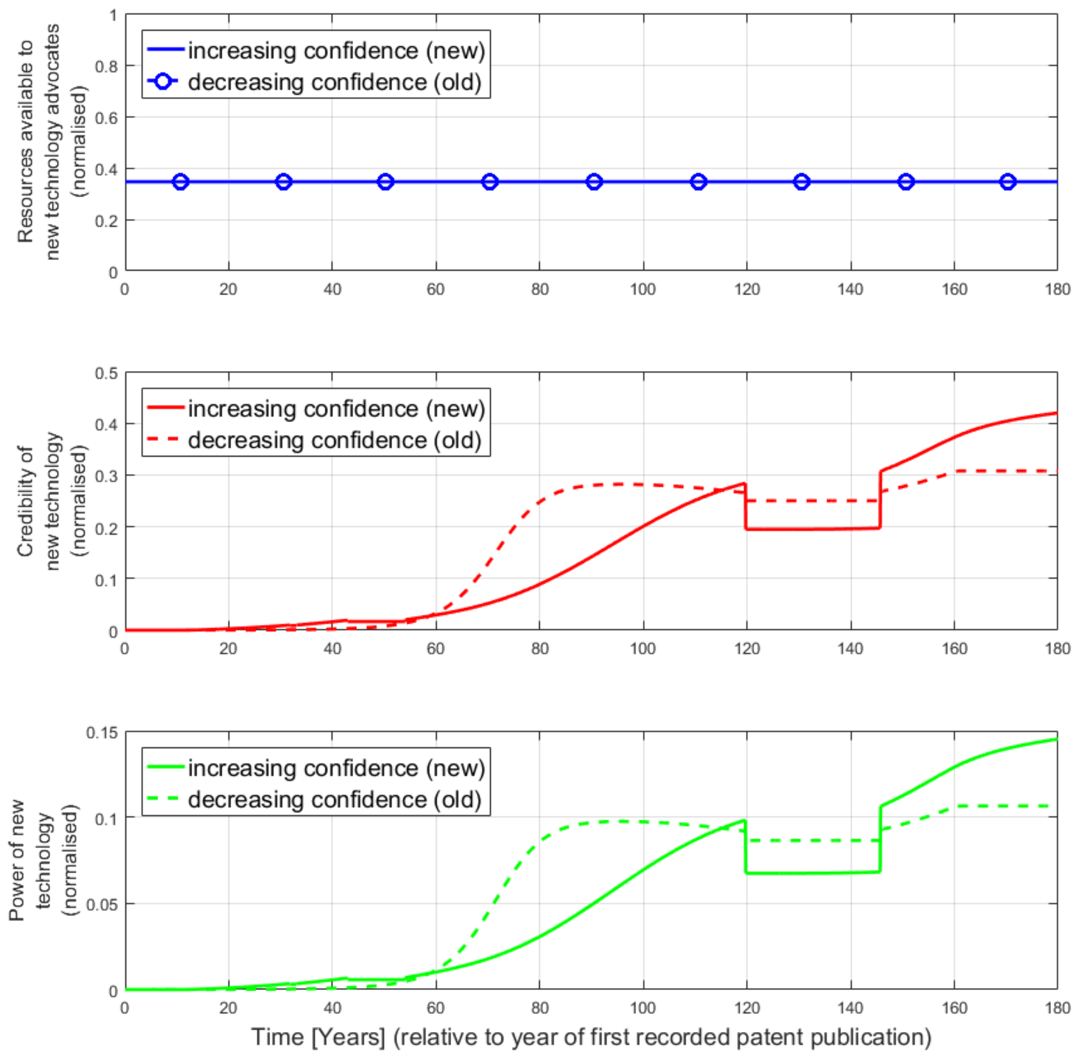


Figure 6.32: Influence of varying confidence levels on the power of new technology advocates

claimed extension opportunity. The current model uses a normalised scale to represent this term, with *0* indicating that there is no supporting rationale or justification behind an advocate's promotion of the extension opportunity, and *1* indicating that the argument is completely convincing (which is unattainable in reality). Persuasiveness is assumed to increase as uncertainty surrounding the extension opportunity reduces, based on the increased utility of a better defined technology roadmap, which leads to reduced risk averseness [Rogers et al., 2005, Chatterjee and Eliashberg, 1990, Dattée and Weil, 2007]. Visibility of scientific and technological development efforts is required to obtain some insight into the possible extension opportunity, explaining the link to persuasiveness mentioned in section 6.4.1 (point 15). However, as expectations of technological gains are often slightly out of phase with actual developments due to communication lag (the 'Productivity paradox' that can cause patterns of surprise, disappointment, and hype etc.), a small 6 month delay is accounted for in line with the findings from Dattée [Dattée and Weil, 2007, David, 1991, Ruttan et al., 2008]. The perceived stagnation of either scientific or technological development efforts then suggests that the extension opportunity claim is not currently credible, and results in persuasiveness dropping to zero in the model, as in Figs. 6.33

and 6.34. This is an over-simplification in the current model, as realistically persuasiveness is more likely to increase and decrease gradually. Consequently, whilst this binary representation makes it easy to identify periods when the extension opportunity of the new technology appears limited, this should be replaced with a more realistic representation in any later extensions. Ultimately, any drop in persuasiveness slows the rate of adoption in the model.

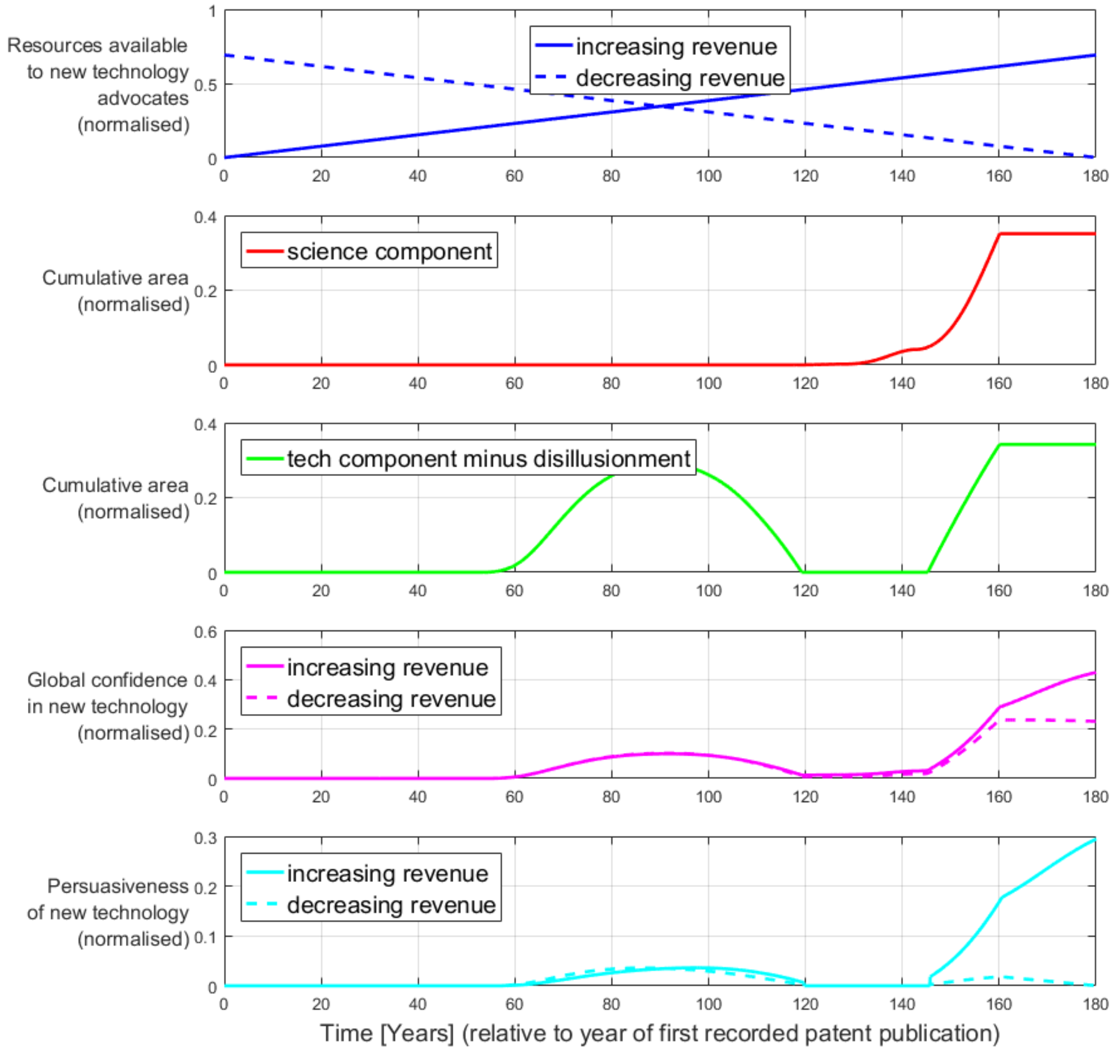


Figure 6.33: Influence of varying revenue generation scenarios on the persuasiveness of a new technology

Lastly, the *size of the new technology's sphere of influence* describes the fraction of the market over which the new technology advocates have control, and consequently, the degree to which the population can be steered to adopt the new technology. Having a large sphere of influence, either through direct control (as in many organisations) or indirect means (such as a strong marketing presence), accelerates the rate of adoption [Bass, 1969, 2004, Constant, 1973, Harty, 2005, Lunenburg, 2012]. In a similar manner to French and Raven's framework on the sources of power, the sphere of influence is assumed to arise from an individual's control of resources or their credibility, as shown in Figs. 6.35 and 6.36, but in this instance control of resources is not a prerequisite for growth in the sphere of influence (point 16

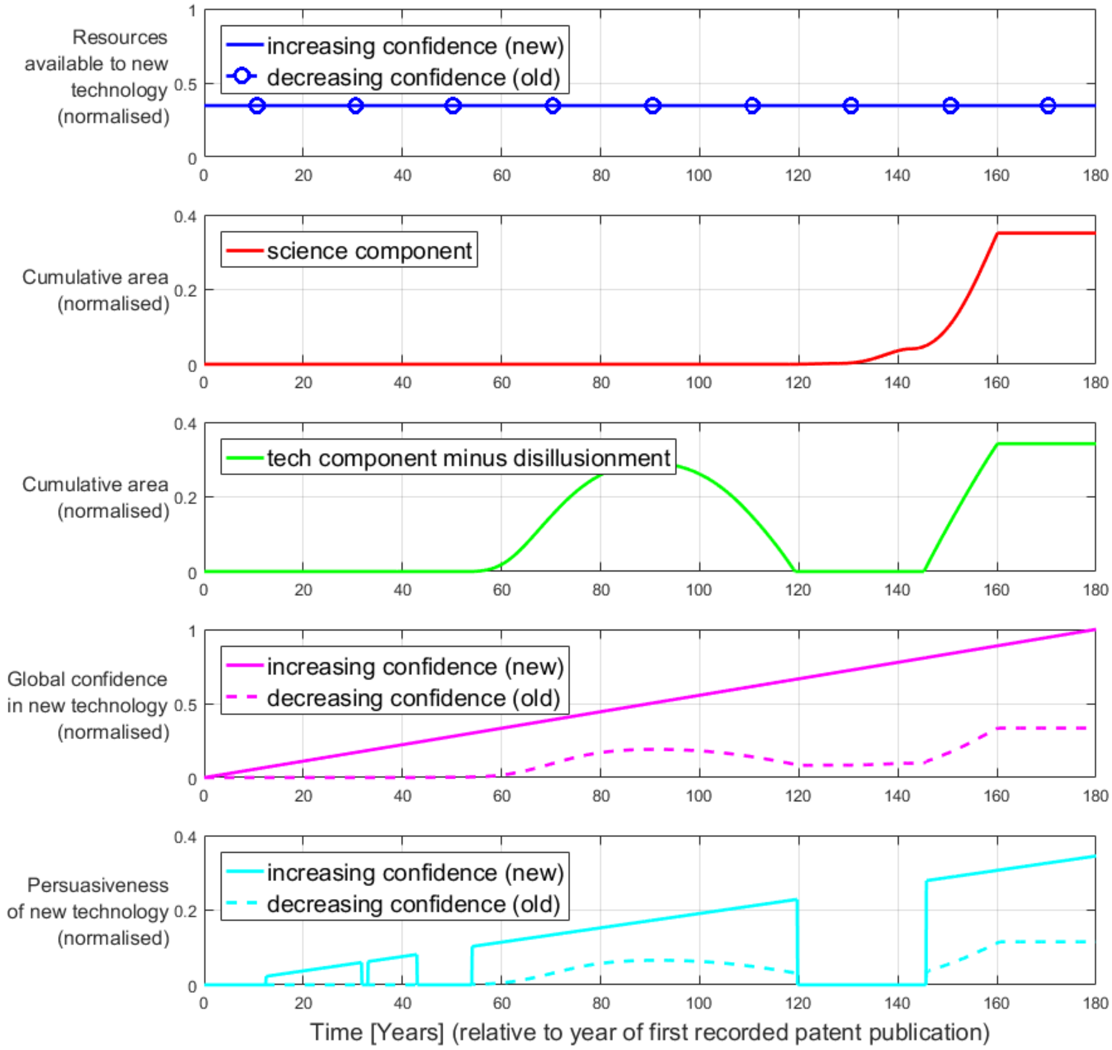


Figure 6.34: Influence of varying confidence levels on the persuasiveness of a new technology

in Fig. 6.30). This is because growth in credibility is observed to increase the likelihood of influencing a wider population in its own right (point 21) [Constant, 1973, Rogers et al., 2005].

Together, these three model variables govern the advertising effectiveness of communications targeted at potential adopters. Fig. 6.37 illustrates the impact on each of different revenue generation scenarios for the new technology, and corresponding responses in the rate of adoption. From this, favourable revenue generation scenarios are seen to increase the modelled effectiveness of these factors. Consequently, targeted advertising is more successful at accelerating adoption in these conditions. In this instance, these factors increase simultaneously, providing the maximum acceleration to diffusion. Nevertheless, an increase in any of these would stimulate faster adoption providing that scientific and technological development efforts support a credible extension opportunity for the new technology. By contrast, Fig. 6.38 shows that a decline in confidence in the incumbent technology is more effective, as modelled, at increasing adoption rates than favourable confidence in the new technology. In this condition, the power and sphere of influence of the new technology increases rapidly. However, the

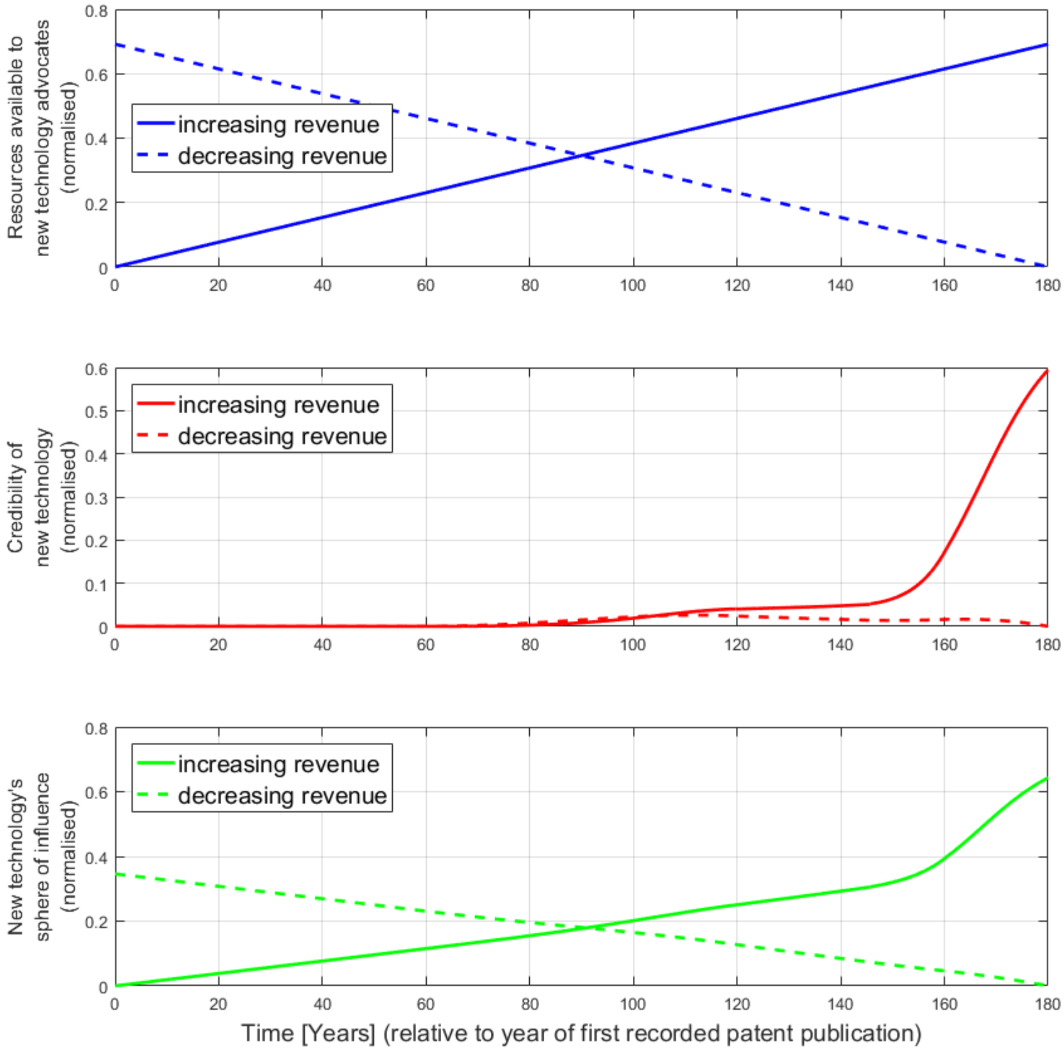


Figure 6.35: Influence of varying revenue generation scenarios on a new technology's sphere of influence

persuasiveness of the emerging technology itself is questionable, as it is not being sold on the merits of its own extension opportunity, but instead on the failure of the previous technology.

By comparing adoption rates predicted for the conditions in Figs. 6.37 and 6.38, it can be seen that opposing scenarios regarding confidence in new and existing technologies has a greater influence on the variability of technology diffusion rates, as modelled, than opposing revenue generation scenarios for the new technology. This is shown in Fig. 6.39, and implies that the model is more sensitive to functional-failure of the existing technology than resource dependency of the new technology.

Resource dependency is accounted for in several parameters in the simulation. The first two of these are the *population size* and *market carrying capacity*. Fig. 6.40 illustrates that in the fully assembled technology substitution model, increasing the population size gradually prolongs the time for presumption and adoption to diffuse through the population. The simulation approximates the global resources available to individuals, based on population size, using a normalised logistic function (given

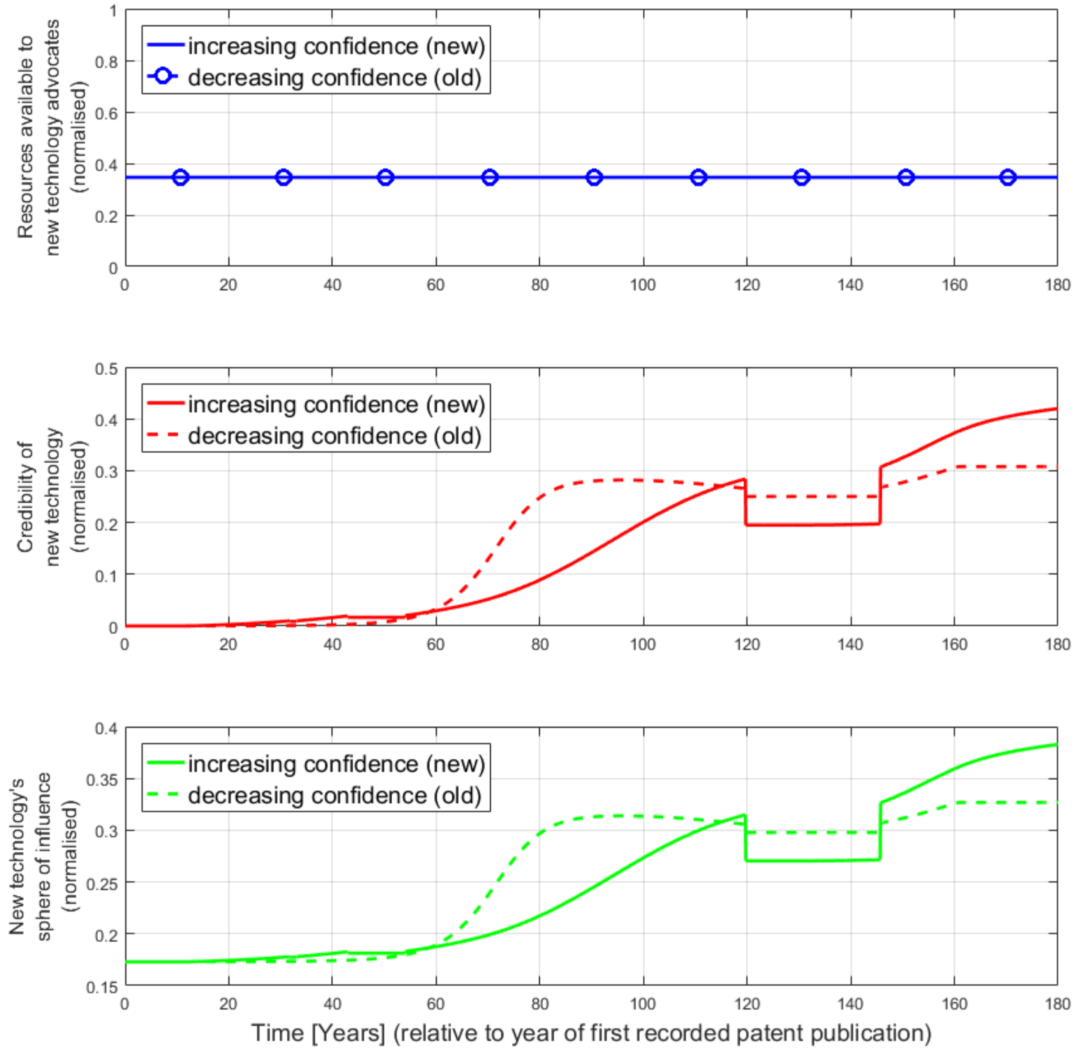


Figure 6.36: Influence of varying confidence levels on a new technology's sphere of influence

in Table F3 in Appendix F), where *0* indicates resource scarcity and *1* indicates plentiful supply. As such, when the population size is far below the market carrying capacity, the logistic function remains at *1*, and the resources available to advocates supporting the new technology are only dependent on their financial situation and confidence levels in the new and existing technologies. However, as the population approaches the market carrying capacity (or alternatively, as the market carrying capacity is reduced as in Fig. 6.41), the resources available to the population start to reduce, which makes it increasingly difficult for supporters of the new technology to acquire the resources and investment needed to secure their new framework (point 17). Consequently, as their resources decrease, so too does their power, persuasiveness, and sphere of influence (shown in Figs. 6.31, 6.33, and 6.35 respectively). These three factors directly contribute to a reduction in the *coefficient of external influence* in the Bass diffusion model, resulting in a reduced fraction of the population adopting the new technology. The *coefficient of internal influence*, (representing *word-of-mouth* effects) is represented by the lack of interest to buy the existing technology in the next sub-model, and corresponding decline in confidence. Notably, the fraction of the population presuming that a technological substitution is

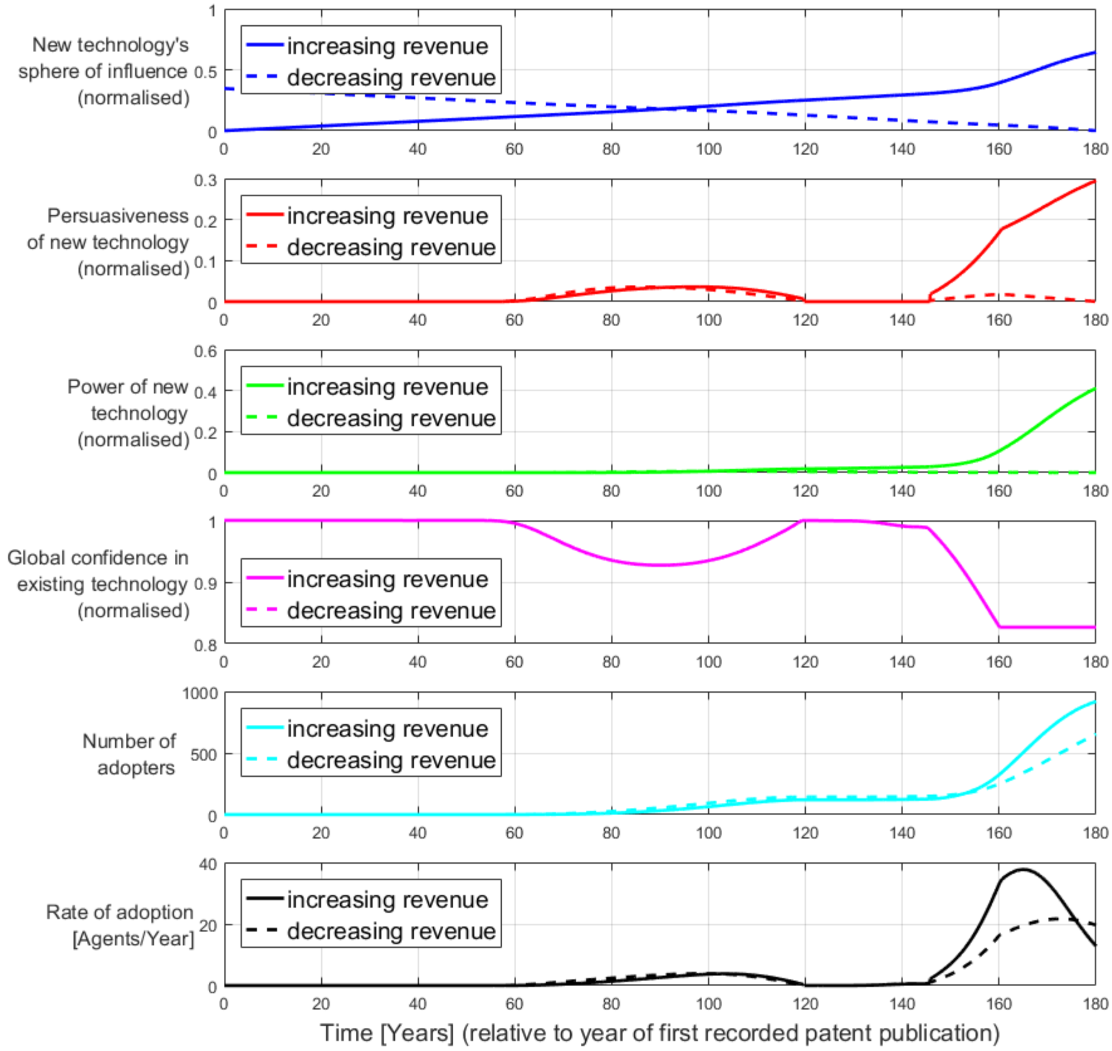


Figure 6.37: Influence of varying revenue generation scenarios on a new technology's rate of adoption

required is unaffected by a reduction in market carrying capacity, as the recognition of a current or future market for a new technology is not limited by financial constraints, even if acquisition of the new technology is. This is in contrast to the adoption fraction, where a larger market carrying capacity enables faster transitions. When resources are plentiful, the modelled financial dependencies enable the devaluing of skills and resources, making it easier for new technologies to establish a foothold (point 18). As such, these sensitivity studies illustrate how financial resource dependency propagates through the simulation, but it is otherwise assumed that economic effects are captured indirectly within the science and technology patent profiles (see chapter 5 for further details on this point).

The credibility of a new technology is established through several mechanisms in the model. First, proof of commercial viability appears as new technology adopters begin to demonstrate favourable revenue generation conditions compared to the existing technology. When this happens, they start to win over strong financial backers who inspire others to put their faith in the same opportunity. The second route to credibility arises from solid scientific and technological rationale for the new technology, which supports the claimed extension opportunities made by its advocates. This is

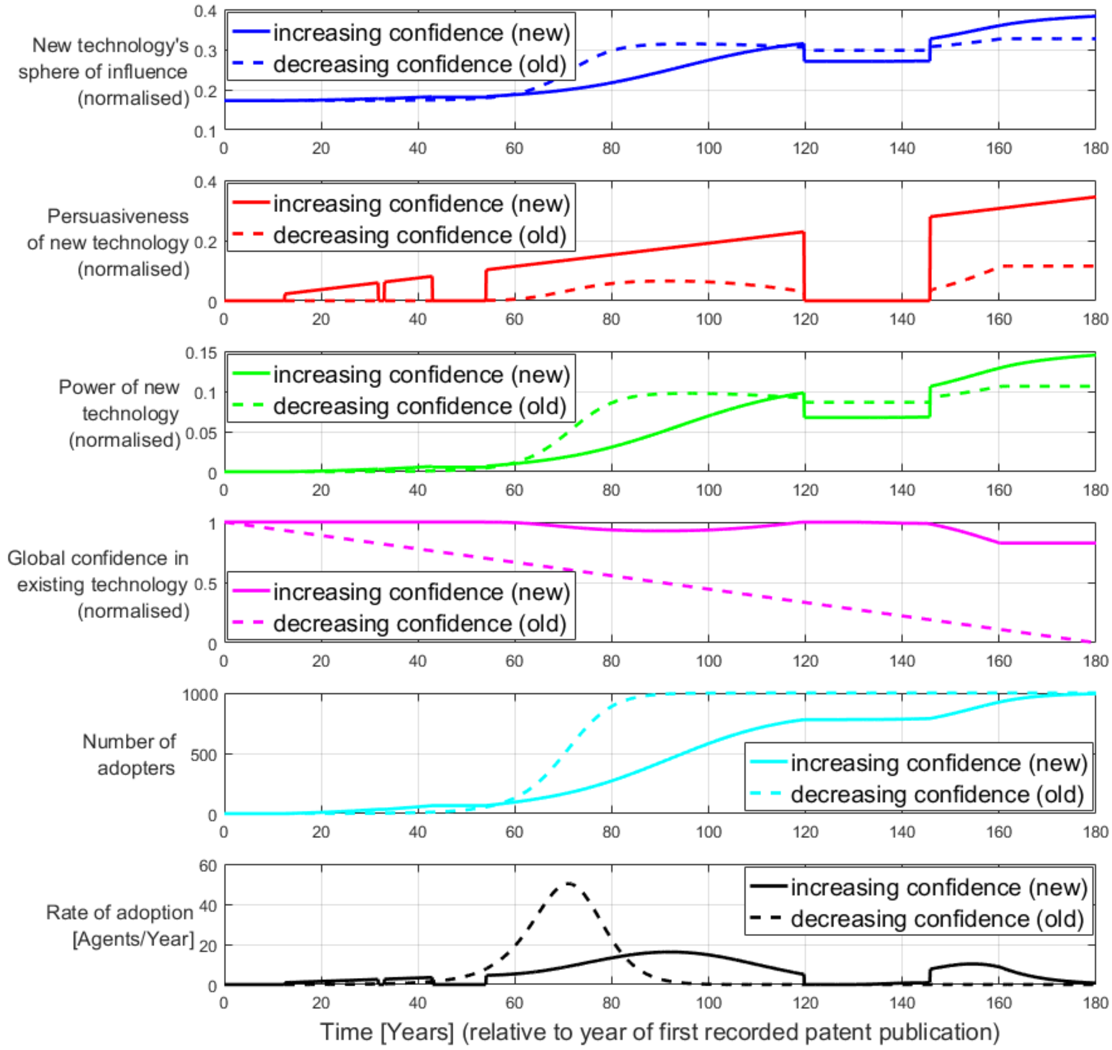


Figure 6.38: Influence of varying confidence levels on a new technology's rate of adoption

provided in the model by the persuasiveness of the new technology (discussed above). The last route is based on the degree of cultural similarity or difference shared by the population (also known as homophily or heterophily), where a greater degree of similarity encourages association with the ideas promoted. This means that individuals are more likely to believe others who share similar values and beliefs. In practical terms in the model, this means that a growing number of adopters increases the likelihood that the new technology will be considered credible by a greater fraction of the population. This also relates to network externalities (or network effect), where the value of using a technology increases as the number of its users grows (point 19). These three mechanisms mean that a new technology earns credibility through 1) demonstrating consistent performance and gaining strong backers; 2) conforming to existing scientific and technological expectations (norms); or 3) enabling social behaviours (point 20) [Rogers et al., 2005]. The effect on these three components and overall credibility, as modelled, under opposing revenue and technology confidence scenarios is illustrated in Figs. 6.42 and 6.43 respectively.

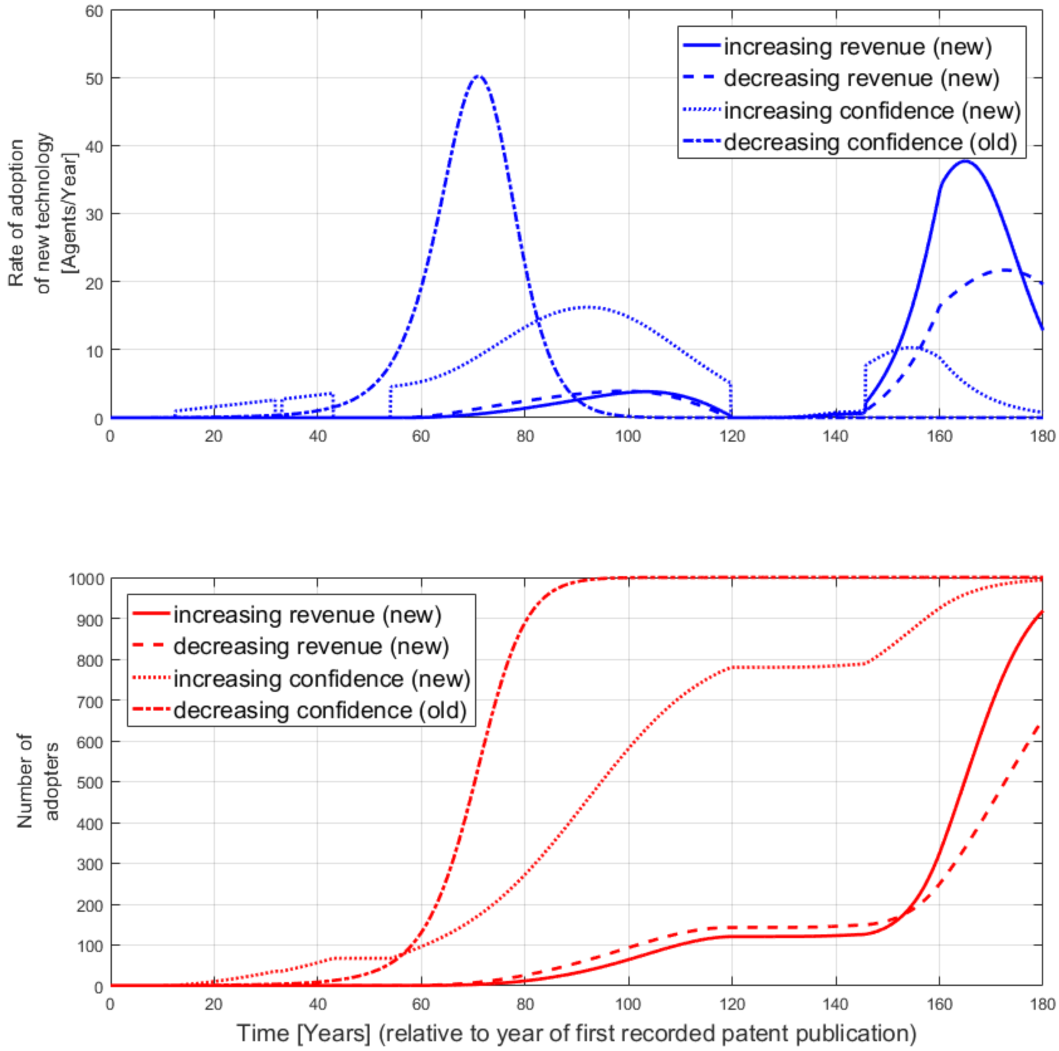


Figure 6.39: Influence of a new technology's rate of adoption on the number of adopters under alternative revenue generation and confidence level scenarios

As a new technology becomes a credible alternative during the substitution process, this reinforces confidence levels associated with it. Through the process of collected referrals, potential adopters decide whether or not to heed the change proposed by existing adopters [Yu and Singh, 2002, Rogers et al., 2005, Dattée and Weil, 2007]. Consequently, as more referrals are generated, they become progressively more credible and confidence in the new technology becomes more robust. This forms part of a confirmation bias feedback loop that addresses how a population tends to bolster evidence that supports the current direction of momentum. More specifically, as confidence in the new technology grows, the rationale behind it becomes more persuasive (i.e. scientific and technological development efforts accelerate, captured indirectly here through the extracted input patent data profiles), leading to improved credibility and further confidence in the technology. This combined influence of development efforts and credibility on confidence in the new technology is depicted in Figs. 6.44 and 6.45. Credibility also represents the experience associated with a new technology. Before *system builders* can create a new technological framework to support further applications and users, sufficient experience in

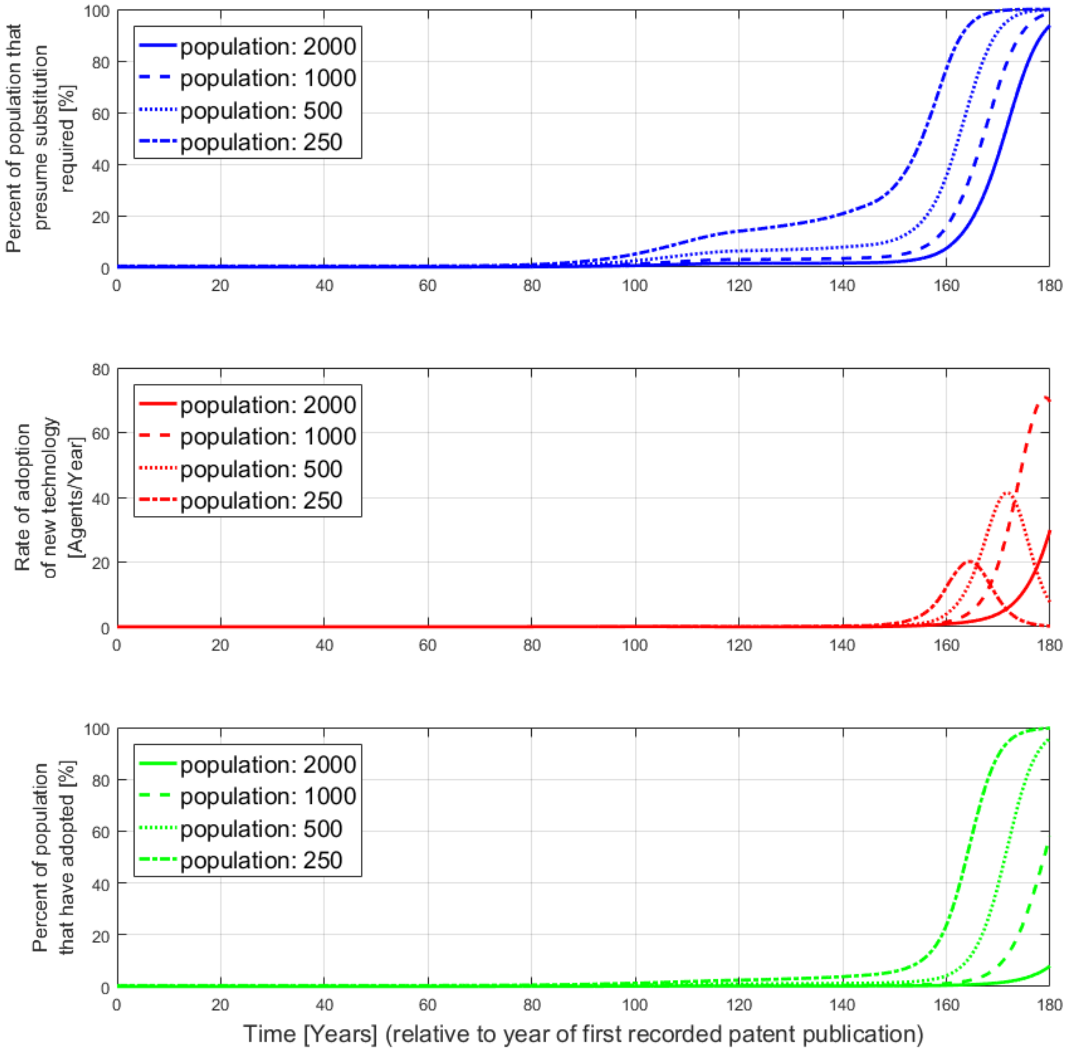


Figure 6.40: Influence of population size on modelled presumption and adoption behaviour

the new technology has to be demonstrated. As such, confidence is gained as experience increases to the point where system builders can begin to create these supportive environments [Hughes et al., 1987].

6.4.4 Model of presumptive influences on confidence

The purpose of the final sub-model (Fig. 6.46) is to account for recognition within the population of the need for technological substitution, based on confidence in the two competing technologies. This model of presumption is adapted from the classic Bass diffusion model in the previous section by modifying the coefficient terms (discussed in chapter 2 and section 6.4.3) that drive the predicted diffusion curves. In this context, the meaning of the second term, the *coefficient of imitation* (q), requires re-evaluation. This coefficient is typically a measure of the social influences between potential adopters and non-adopters, and often considered synonymous with *word-of-mouth* communications. When referring to adoption, *word-of-mouth* describes an existing adopter communicating their experiences to a potential adopter. However, when considering presumption, the person who already

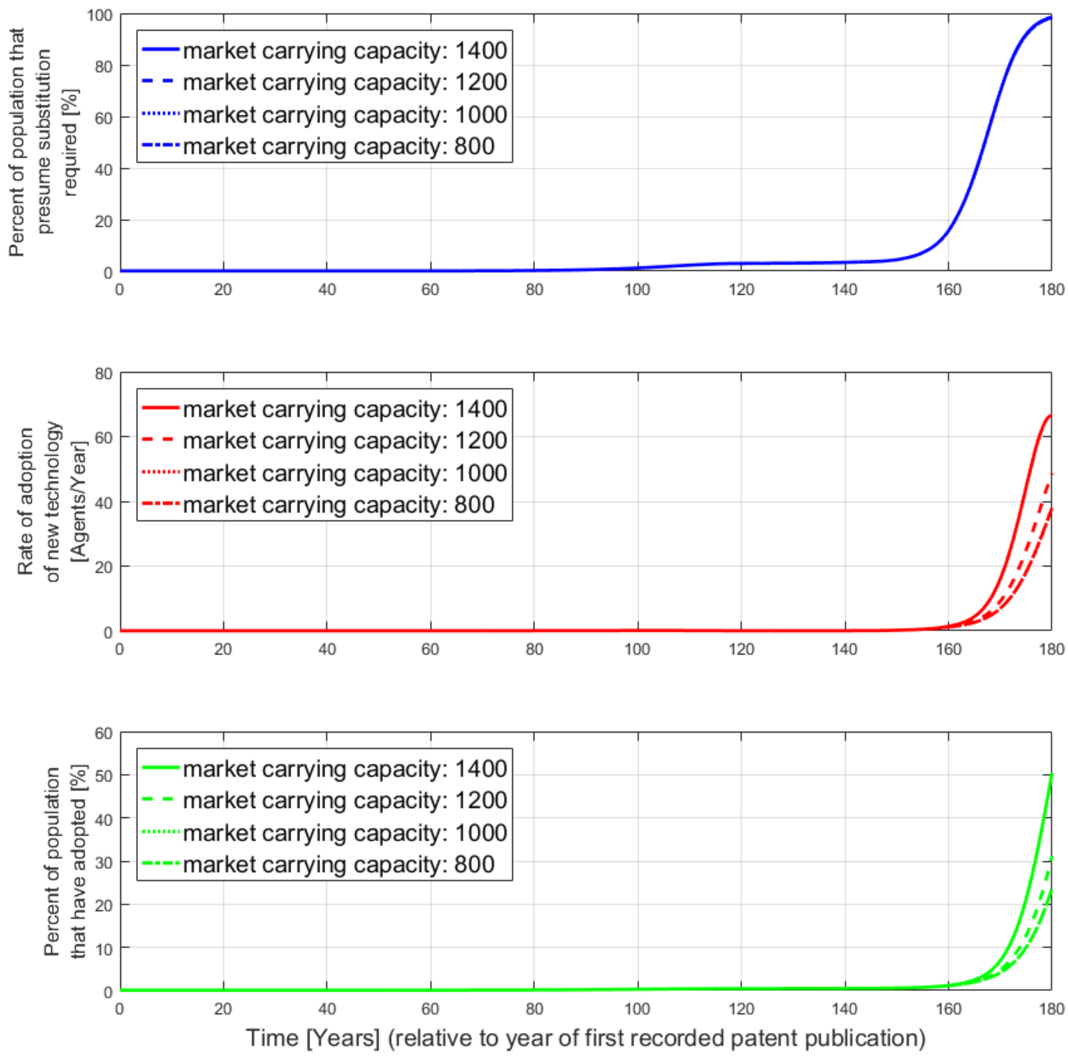


Figure 6.41: Influence of market carrying capacity on modelled presumption and adoption behaviours

presumes that a change is required may not have any experience of the technology (as they have not yet adopted themselves). In this adapted context, *word-of-mouth* is primarily referring to individuals communicating the experience and knowledge of a small group of scientific pioneers currently experimenting with the technology (but not a commercialised product), based on reading academic publications and discussing the new concepts. Consequently, *word-of-mouth* in these instances communicates the quantitative evidence about a new technology from academic publications or patents to a new audience, rather than relaying user-experiences. Equally, academic marketing of scientific and technological developments regarding an emerging technology are targeted at a reduced audience, usually to seek fledgling investment or acknowledgement in a targeted field of expertise before mass commercialisation. The Bass diffusion model is therefore adapted to combine the p and q terms into a single term, representing both dimensions conventionally used to distinguish between directed and social influences. This is due to the restricted scope of targeted academic marketing, and revised definition of *word-of-mouth* communication that in this case reiterates the evidence from directed communications. This revised term is referred to here as the *coefficient of substantiation*.

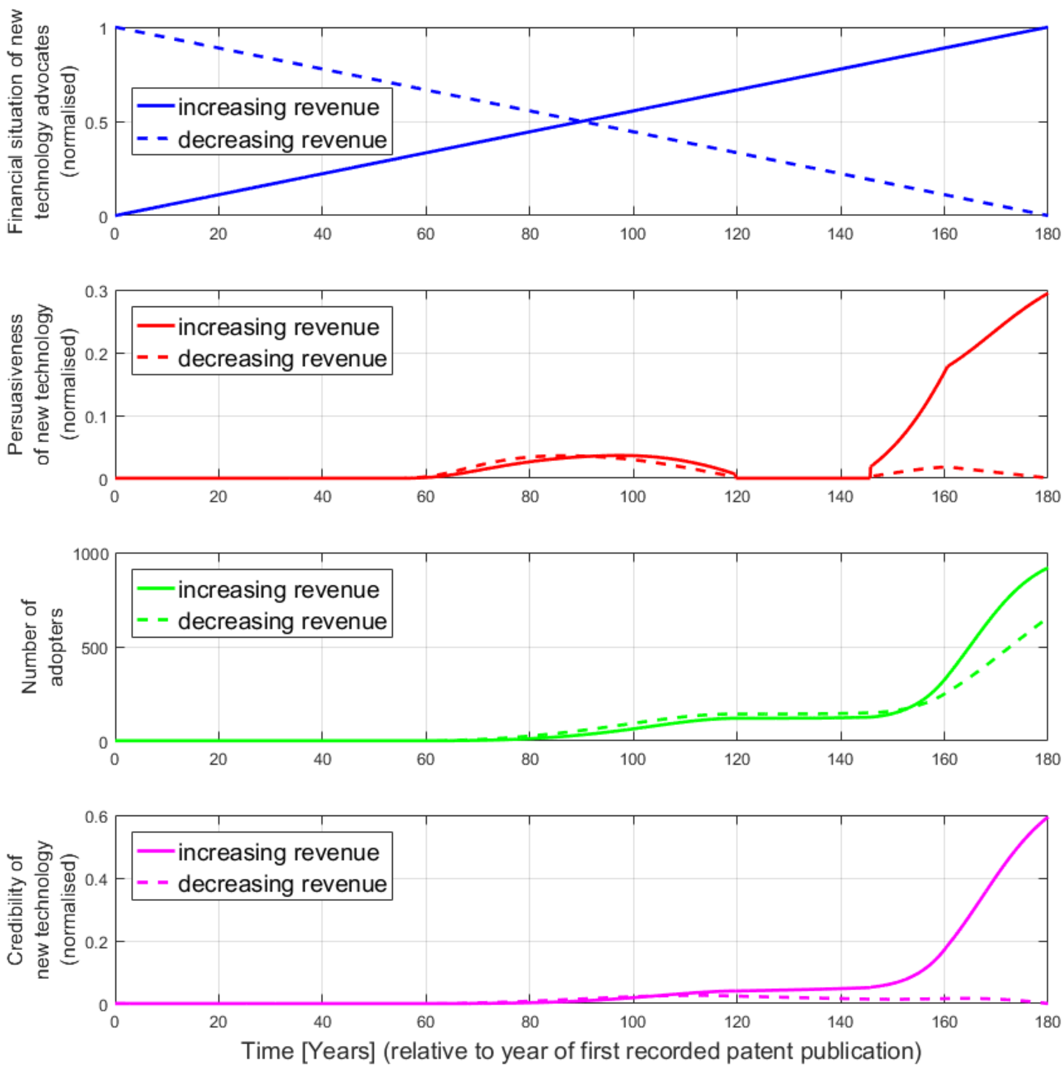


Figure 6.42: Influence of varying revenue generation scenarios on a new technology's credibility

The *coefficient of substantiation* used to determine the rate of presumption is therefore shaped by scientific and technological development efforts towards the new technology, and evidence reiterated by individuals who believe it presents a credible alternative to the existing technology. As such, increasing confidence in a new technology reflects growing evidence supporting the transition to this technology (point 23 in Fig. 6.46), increasing the rate of presumption.

For example, when Alan Arnold Griffith's 1926 paper showed that until this point, compressors and turbine designs had effectively been 'flying stalled', he reinstated confidence in turbomachinery. His evidence provided increased confidence that led to the Aeronautical Research Committee supporting the development of single-stage axial compressors and turbines in a small-scale experiment. From the working testbed demonstrated in 1928, a series of designs were built to test different concepts (to provide more evidence). The scientific evidence therefore reignited confidence in turbomachinery as a means to enable higher performance, which accelerated exploration of this technology within this niche population (similar to the relationship modelled by point 23). At the same time, and as discussed in

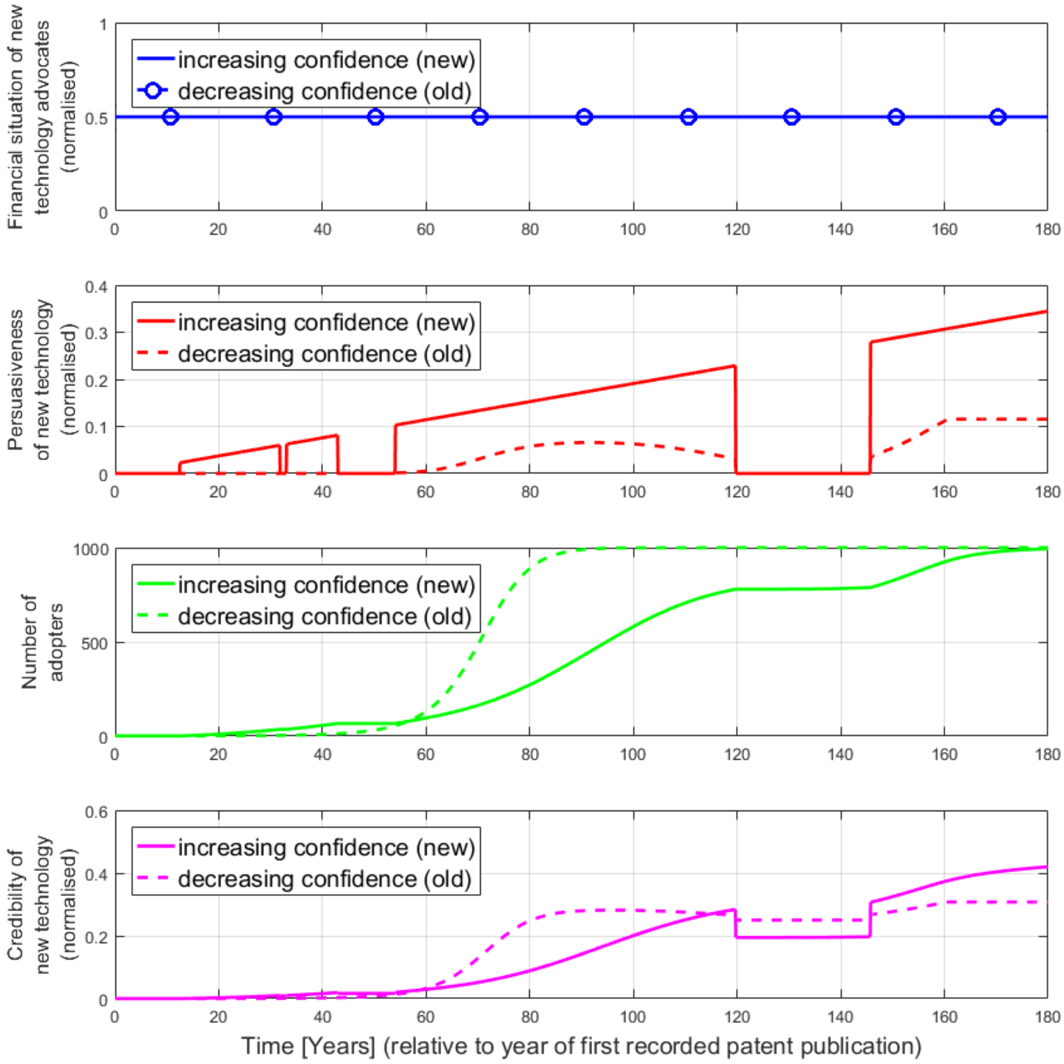


Figure 6.43: Influence of varying confidence levels on a new technology's credibility

section 6.4.1, scientific and technological development efforts linked to a new technology can reduce confidence in existing technologies by providing contradictory evidence. Frank Whittle's thesis describing the need for high altitude, high speed, flight to overcome propeller compressibility effects reduced his confidence in the ability of piston-engined aircraft to achieve greater performance improvements. This led to him developing a turbojet concept. Whittle showed this to colleagues at the air base he was stationed at, gaining support from Flying Officer Pat Johnson and subsequently the base's commanding officer. This illustrates how scientific evidence cast doubt on the capability of the existing technology, which led to reduced confidence in it, and consequently increased the rate of presumption associated with the new technology within a niche population (similar to the modelled relationship in point 8). Conversely, resurging confidence in existing technologies indicates that the new technology will need to provide more substantial evidence to convince individuals of its superior technical and commercial merits (also accounted for by point 8 in Fig. 6.46).

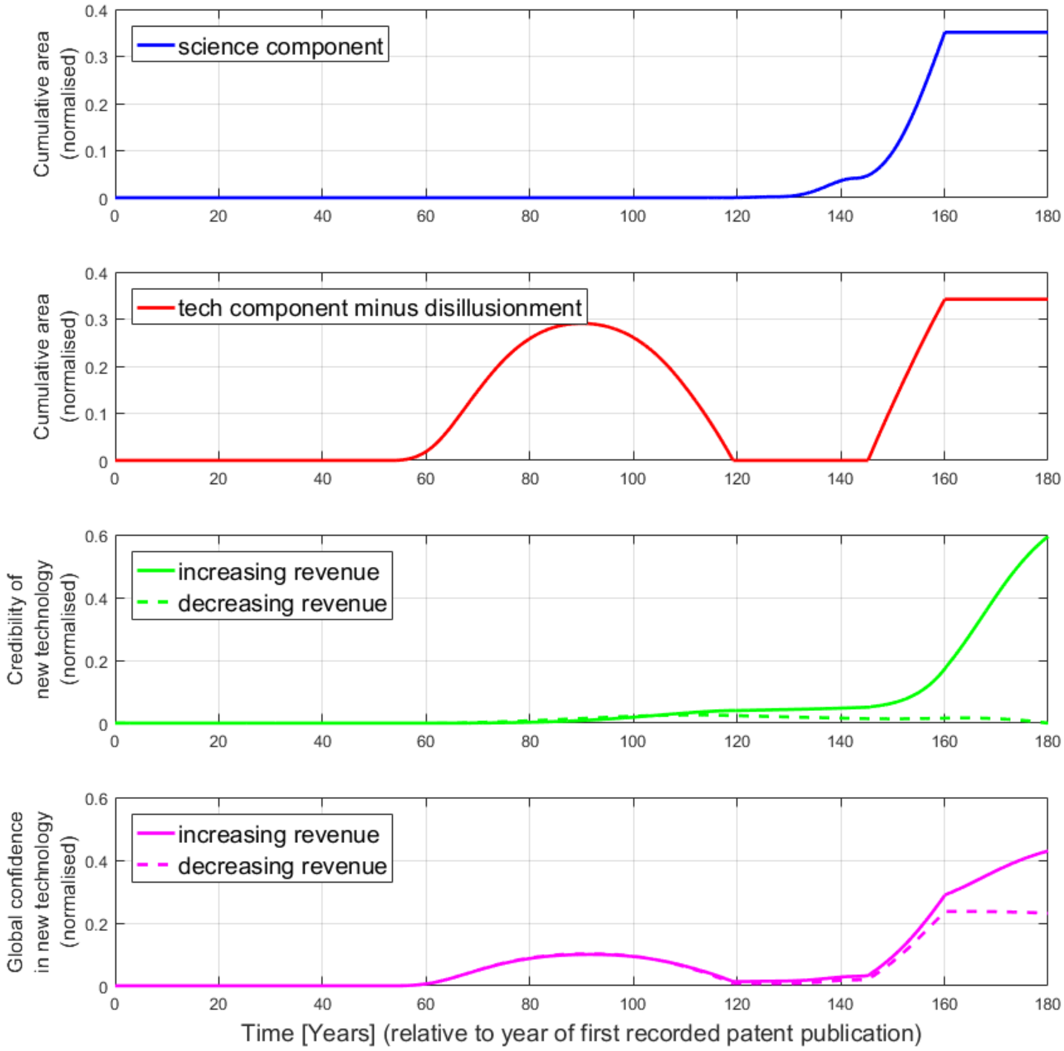


Figure 6.44: Influence of varying revenue generation scenarios on global confidence in a new technology

The reiteration of evidence by individuals who already recognise the need for the new technology means that the rate of presumption becomes non-linear, accelerating as a critical mass of the population supports the idea. This behaves identically to the *word-of-mouth* effects in the Bass diffusion model, where a positive reinforcement loop increases substantiation effects, and consequently, the rate of presumption (point 24). This was observed when Frank Whittle's turbojet patent entered the public domain in April 1931 and was subsequently registered at the Berlin patent office in mid-august 1931. Its details were quickly circulated amongst German aeronautical companies and research organisations.

The impact of these contrasting substantiation conditions (i.e. increasing confidence in the new technology versus decreasing confidence in the old technology) on the rate of presumption is subsequently modelled in Fig. 6.47.

As presumption increases within a population, a corresponding increase is assumed in the lack of interest to buy the incumbent technology (point 25). This provides the first warning that a substitution may

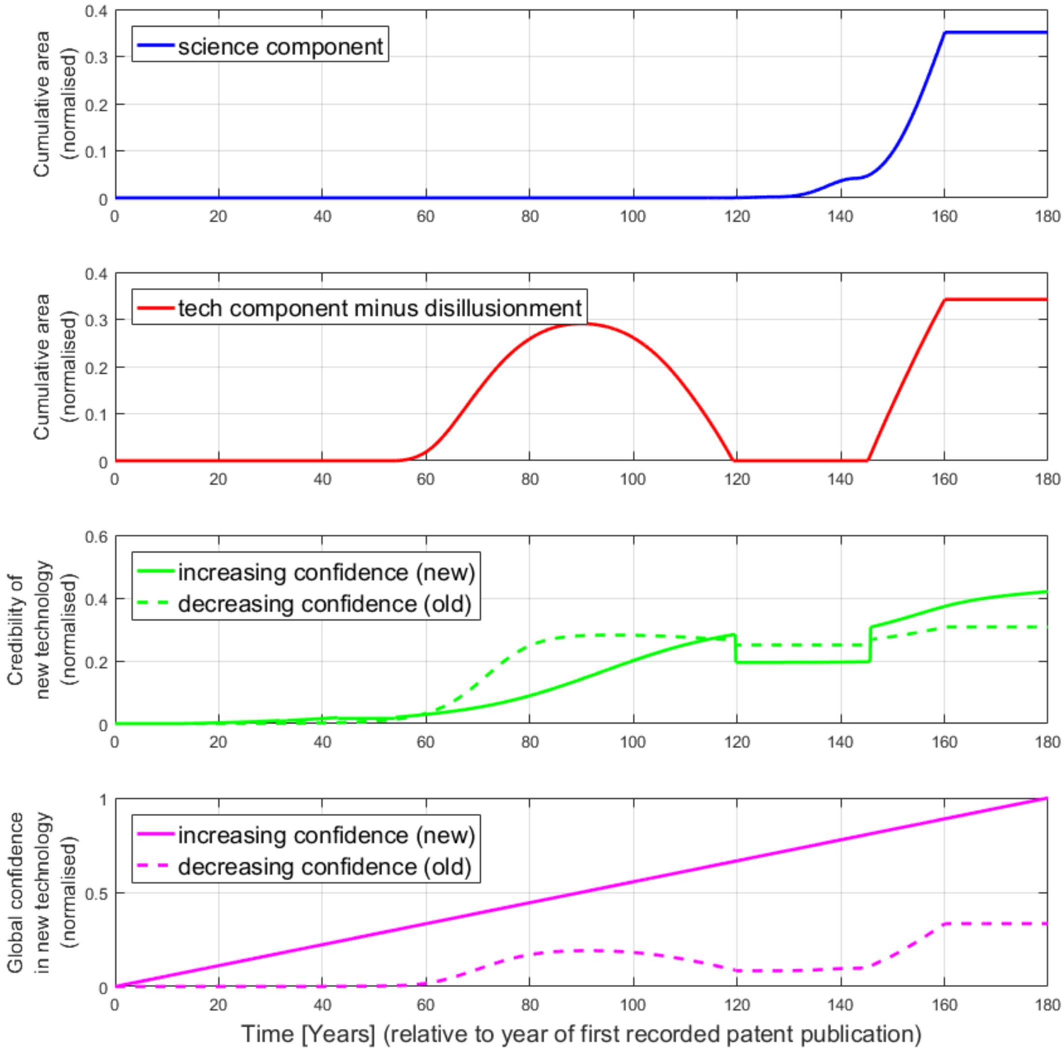


Figure 6.45: Influence of varying confidence levels on global confidence in a new technology

take place, leading to both reduced confidence in the existing technology, and reduced profitability for individuals supporting it (point 26). As the financial merits of the existing technology decline, the financial situation of new technology advocates is assumed to improve through a devaluation of the skills and resources required to build a supporting framework. Such a framework is necessary to convince potential adopters that their performance expectations will be met, and provide reassurance that technology benefits will exceed any foreseen risks or price hurdles (point 27).

Points 25 to 27 in the model can be illustrated by the reaction of UK engine manufacturers following the successful demonstration of the Gloster E.28/39 in April 1941 (powered by a Power Jets' W.1 engine), which overtook conventional piston-engined aircraft performance within days of its first full flight. At this time, nearly every engine company in Britain then launched efforts to develop their own turbojets, diverting funds from piston-engine projects to support these programmes [Hawthorne, 1989, Mandeles, 1998]. Whilst the revaluation of piston and turbojet design skills was not necessarily true of Power Jets Ltd (which continually struggled to make money and was eventually nationalised), it is true of the

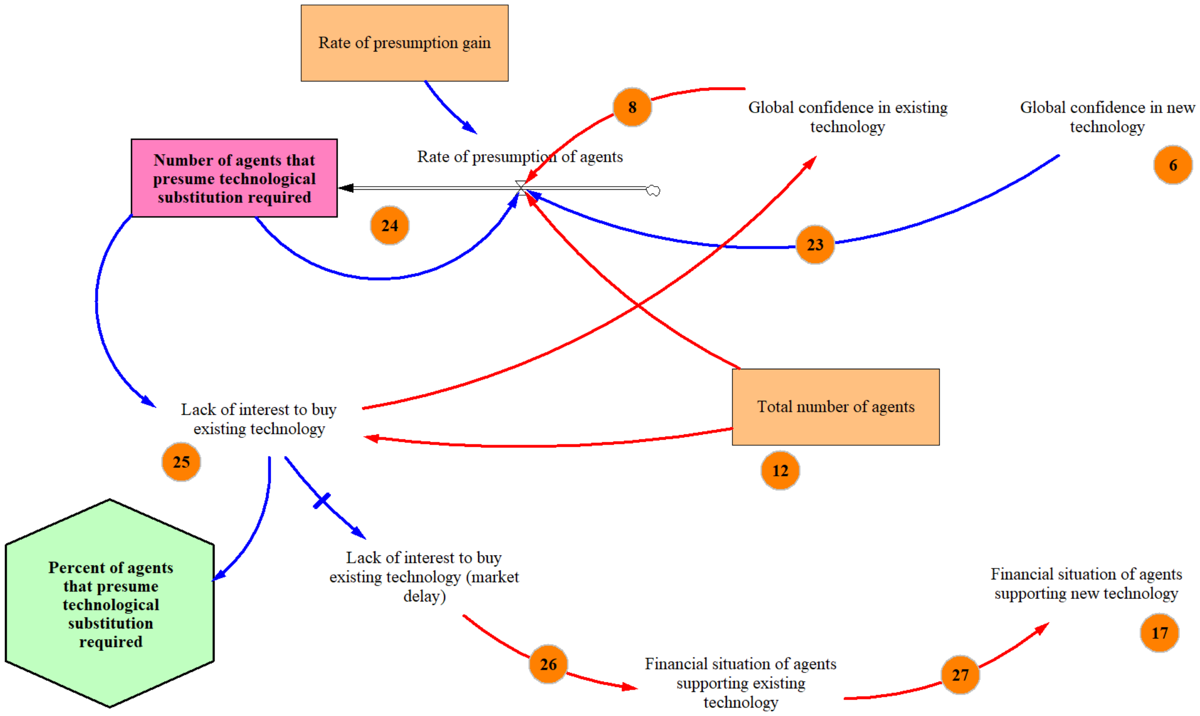


Figure 6.46: Presumption model taking into account confidence levels in both new and existing technologies

wider propulsion market (in this case, other UK engine manufacturers), which quickly established new jet research divisions and production lines.

For simplification, in this model a zero-sum resource and skills competition has been assumed (illustrated in Fig. 6.48), which does not take into account resources being diverted to external markets. Although in reality this is not usually the case, the sensitivity of technology diffusion to extreme resource dependency scenarios in Fig. 6.39 (shown by revenue curves) suggests that this is unlikely to affect the timing of the adoption take-off. However, this feature could be improved in future developments.

As illustrated in section 6.4.3, an increase in resources provides new technology advocates with greater power, persuasiveness, and sphere of influence. These factors correspond to the *coefficient of innovation* (p), in the Bass diffusion model that contributes to the rate of adoption. Reduced confidence in the existing technology, arising from a reduction in sales, also feeds directly into *word-of-mouth* effects within the rate of adoption (i.e. the *coefficient of imitation*, or q term). Therefore, presumptive effects contribute to both coefficients in the rate of adoption. By contrast, functional-failure effects only impact confidence in the existing technology in the model. Consequently, technological failures are limited to influencing the *coefficient of imitation* term in the Bass diffusion model. This means presumption has two routes to increase adoption rates for the new technology, whilst technological stagnation only has one. More generally this equates to confidence in a new technology contributing to the rate of adoption indirectly in the model, whilst confidence in the existing technology is observed to have a direct effect.

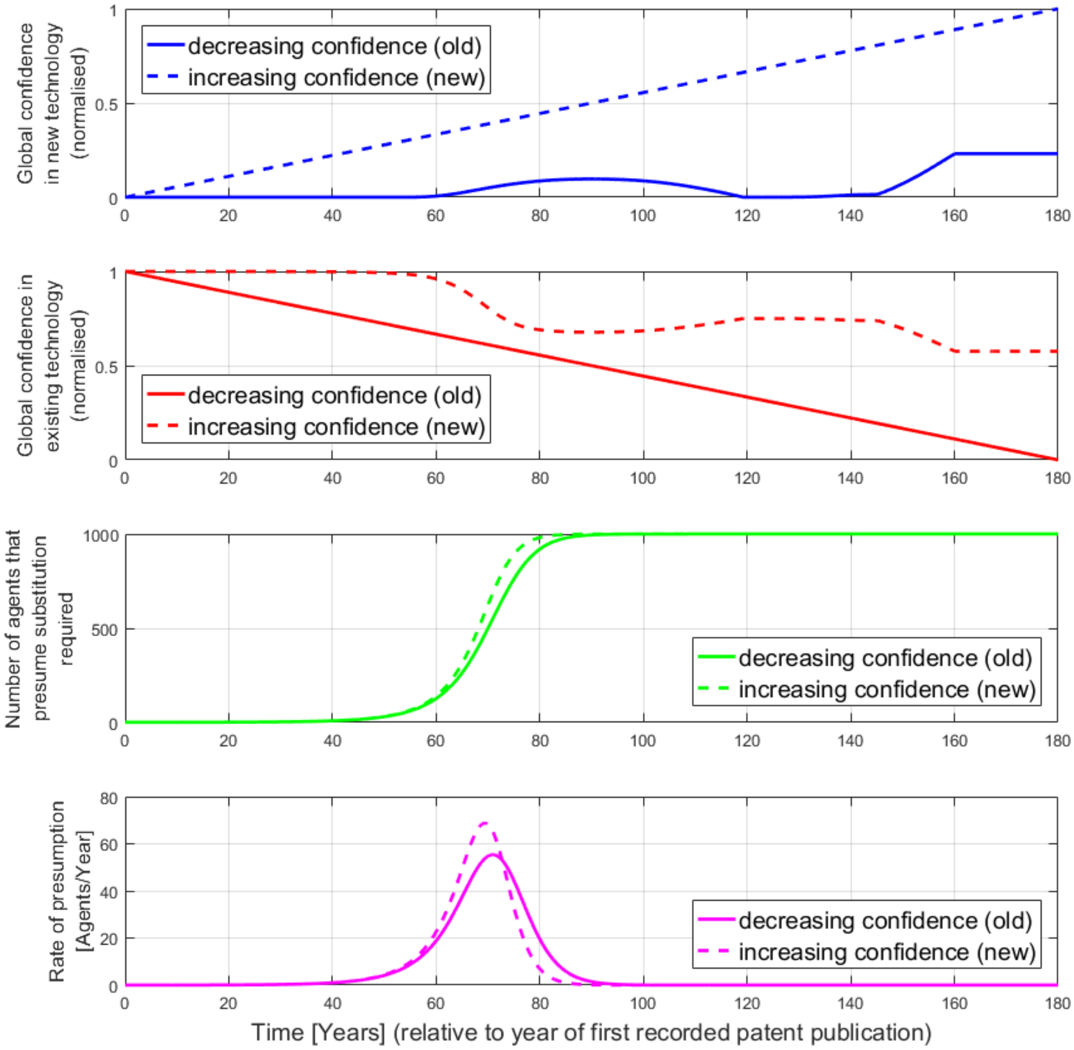


Figure 6.47: Influence of varying confidence levels on the rate of presumption

When confidence in the existing technology decreases rapidly, unaccompanied by increased confidence in the new technology (as artificially induced in Fig. 6.49), this can create an 'upset' technological failure scenario in the model where substitution is virtually unanticipated by the population. This resembles the *resilience illusion* mode described by Adner [Adner and Kapoor, 2015], where the market is dominated by a stagnant incumbent. In this condition take-off in adoption occurs earlier as confidence in the existing technology is artificially reduced, whilst the population that recognises in advance the need to move to the technology that eventually emerges as the replacement remains largely unchanged. This is illustrated in Fig. 6.49, where the population that recognises substitution to the specific technology emerging as necessary (solid green line) practically overlaps with the population that has adopted the technology (solid light blue line). This suggests potential adopters may be more uncertain or surprised by the emergent technology. The technology that emerges therefore appears to be adopted by the wider population just as recognition of the need to adopt this specific technology begins to grow. This is encouraged by reduced confidence in the incumbent technology. This effect arises because the model assumes that presumption for a technology is dependent on confidence levels

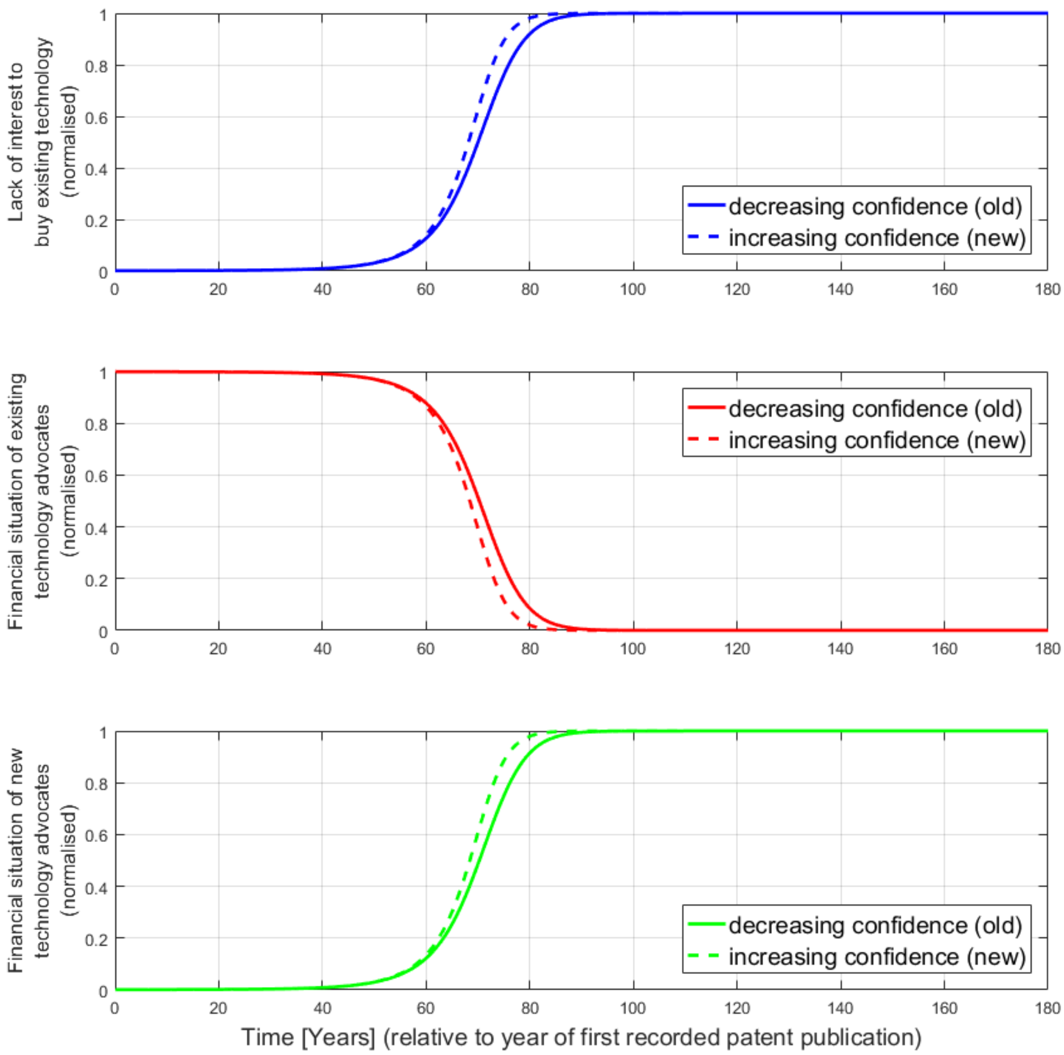


Figure 6.48: Influence of varying confidence levels on the financial situation of new technology advocates

in both the existing technology and the specific technology emerging. At the same time, the rate of adoption as modelled is predominantly determined by the confidence in the existing technology. Consequently, where the emerging technology has not yet demonstrated scientific credibility (i.e. confidence in it remains relatively low), presumption is largely unchanged whilst adoption is reacting to market needs. This effectively represents a market where users eagerly await a replacement for a perceived stagnant technology, but do not know where the replacement will come from. Conversely, when rapidly decreasing confidence in an existing technology is accompanied by a comparable increase in confidence in the new technology, this resembles the *creative destruction* mode described by Adner [Adner and Kapoor, 2015].

6.4.5 Technology substitution model

By combining the market share data in section 6.1 with the sub-models in sections 6.4.1 to 6.4.4, the final technology substitution model is generated. This is shown in Fig. 6.50.

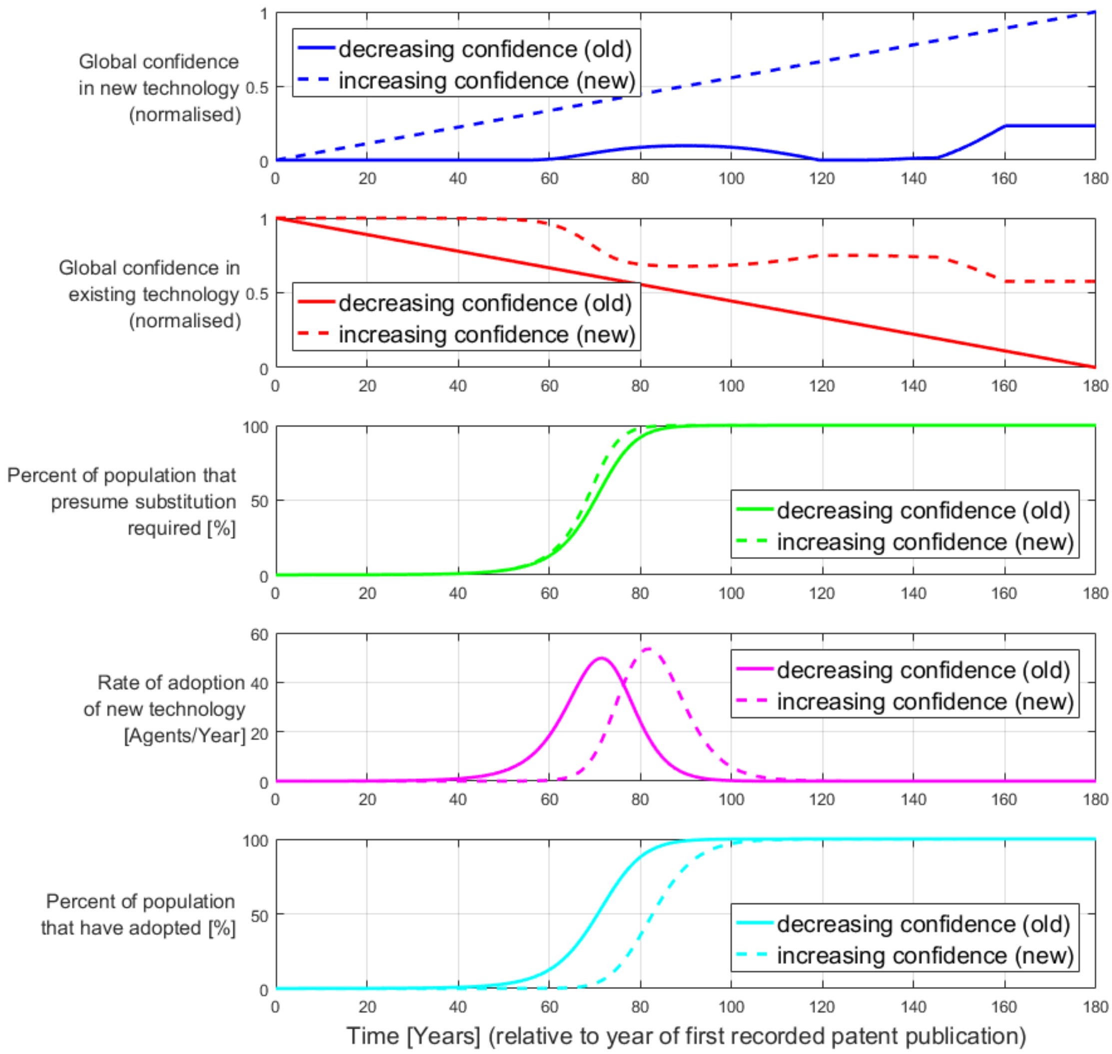


Figure 6.49: Contrasting presumption and adoption behaviours in response to varying confidence levels

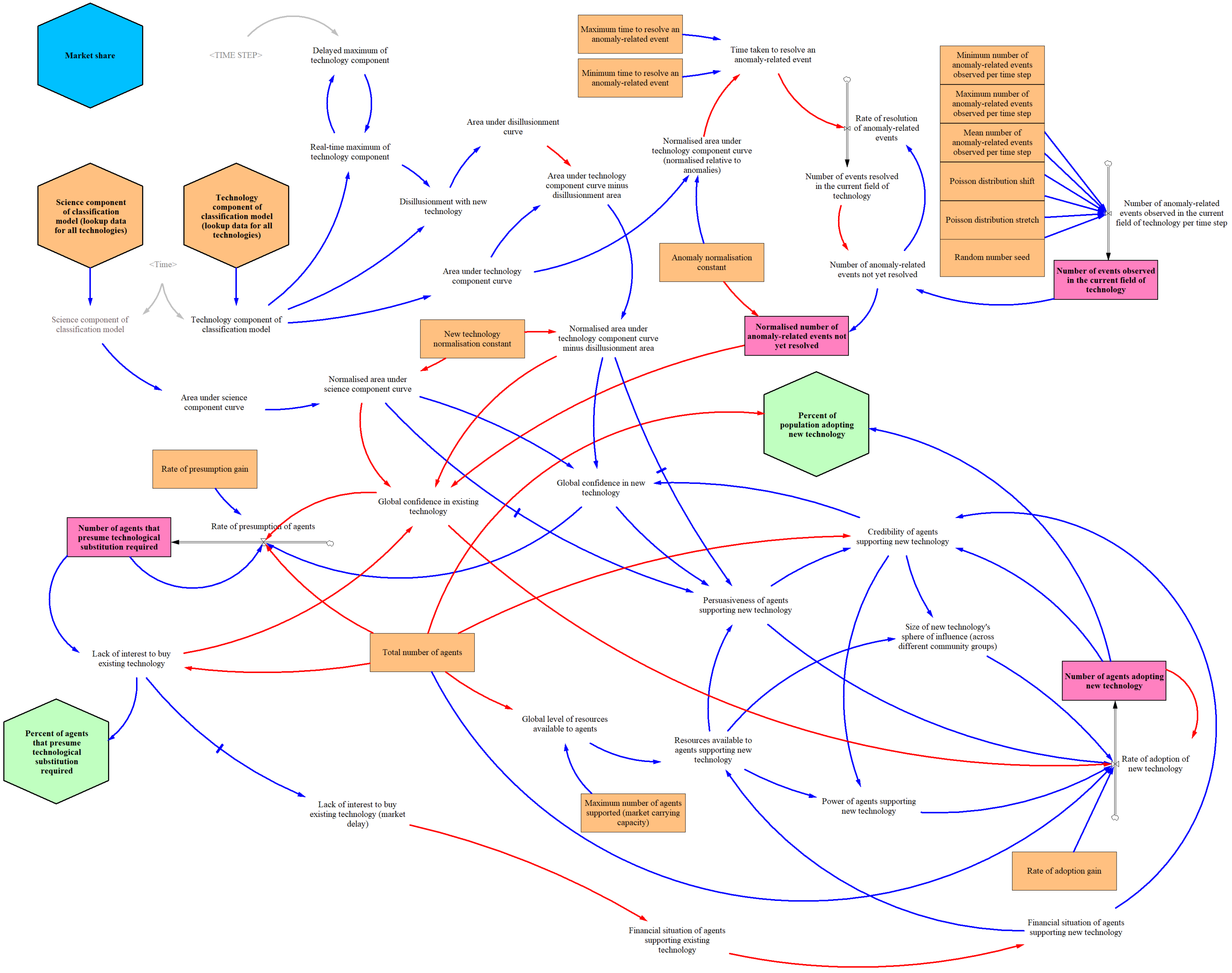


Figure 6.50: Technology substitution model based on selected patent indicators

Table 6.1: Input data profiles used in technology substitution model

Input data profile	Units	Description	Source
Real-world technology adoption curves	Market share [%]	Historic adoption data for the technologies used in model calibration	See Table 4.1 in section 4.2.2 and section 6.1 for details of individual technology sources
Science component of classification model	Patent counts	Weighted functional data object corresponding to scientific development activities (i.e. cited references by priority year) associated with the new technology	Calculated as the element-by-element multiplication of the functional linear regression coefficient and original count values for cited references by priority year. Original count values extracted from the Questel-Orbit FamPat database (see section 4.2.1)
Technology component of classification model	Patent counts	Weighted functional data object corresponding to technological development activities (i.e. number of non-corporate assignees by priority year) associated with the new technology	Calculated as the element-by-element multiplication of the functional linear regression coefficient and original count values for the number of non-corporate assignees by priority year. Original count values extracted from the Questel-Orbit FamPat database (see section 4.2.1)

A summary of input data profiles used in the fully assembled model is provided in Table 6.1, whilst details of all other user-defined and auxiliary variables (with their causal relationships), and equations used in the Vensim model are in Tables F2 to F4 (Appendix F).

6.5 Model verification

Based on the main behavioural criteria discussed in sections 2.9 and 6.4, the simulation model requires traits a), b), and c) to be present for a new technology for adoption to be driven by presumption. This is not required for recognition of either a possible future limiting condition for the existing technology, or the spontaneous emergence of an alternative technology, which can arise from trait a) or b) respectively. The impact of traits a) to c) is seen in Fig. 6.51, where the science and technology components are first independently, and then concurrently, set to zero (whilst events associated with technological anomalies are set to dissipate instantaneously to prevent reactive substitutions from occurring), resulting in progressively more significant reductions in adopters by the end of the simulation. As the rate of presumption reduces from one condition to the next, it shifts the peak of the technology adoption curve back by an increasing number of years. This provides a means to further quantify presumptive effects through calibration of the substitution model to the categorised real-world adoption curves in section 6.1. Where a technological failure is not present for the existing technology and there is no presumption associated with the new technology (arising from an absence of observed scientific or technological development efforts), new technology adoption is non-existent.

By contrast, in reactive substitutions, adoption is driven by a perceived functional-failure in the existing technology, indicated by an accumulation of anomaly-related issues highlighted by the emerging alternative. This dual-mode adoption behaviour is observed by setting the science and technology

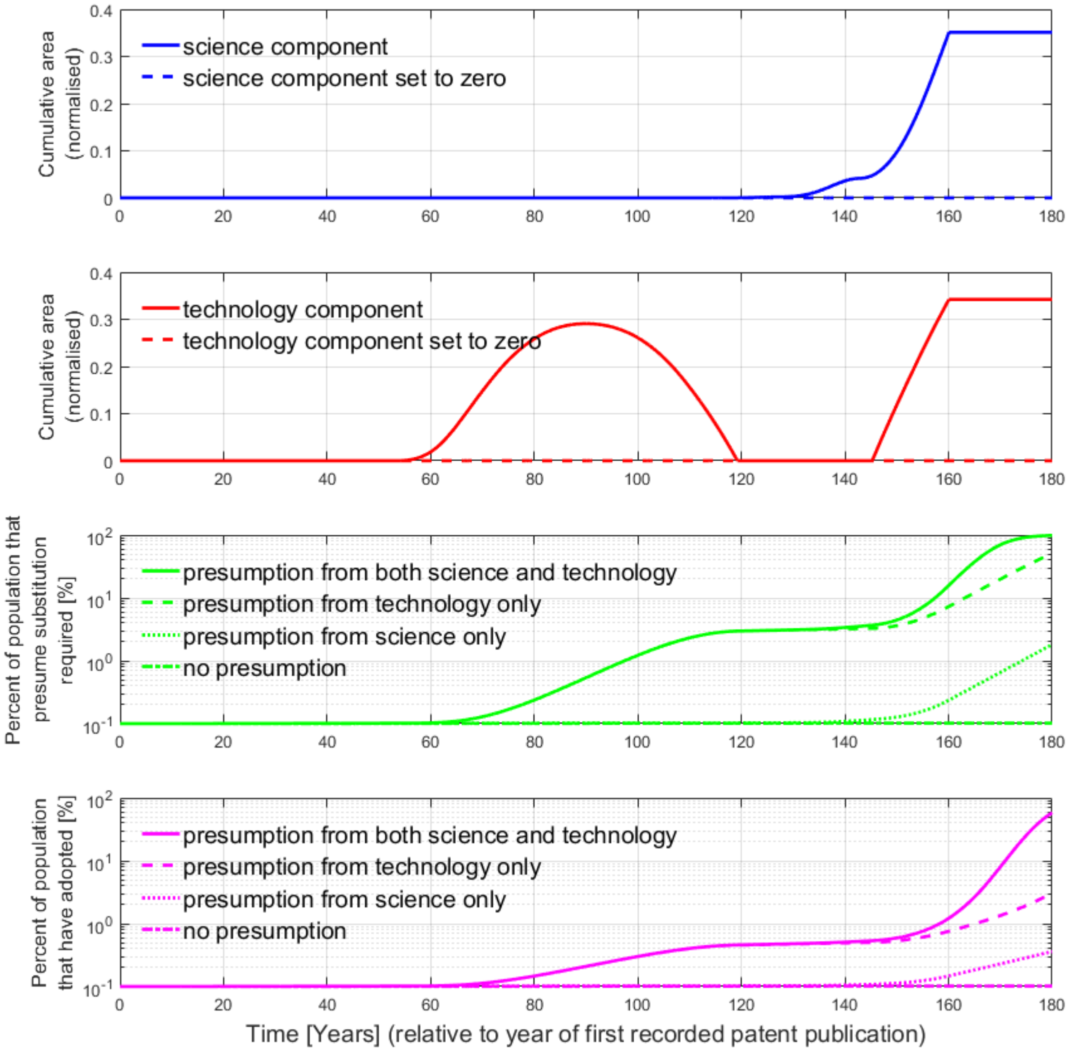


Figure 6.51: Dependency of modelled presumptive substitutions on scientific or technological development efforts

components for the new technology to zero (so that only the existing technology is considered), whilst increasing the time to resolve anomaly-related events and/or their frequency of occurrence. The expected behaviour is demonstrated in Fig. 6.52 where as the number of events accumulates (rather than being promptly resolved to maintain a steady level), the adoption rate increases significantly due to depletion of confidence in the existing technology. Even in conditions where anomaly-related events are quickly resolved (so that there is a low level of accumulation), some adoption of the new technology still occurs. This again results from a perceived technological failure, but here the sentiment is only shared by innovators and some early adopters, as the case against the existing technology is not yet convincing for the wider population.

By combining the adoption behaviours in Figs. 6.51 and 6.52, the technology substitution model can be calibrated to represent both substitution modes by switching between alternative values for the *maximum time to resolve an anomaly-related event* and *mean number of anomaly-related events observed per time*

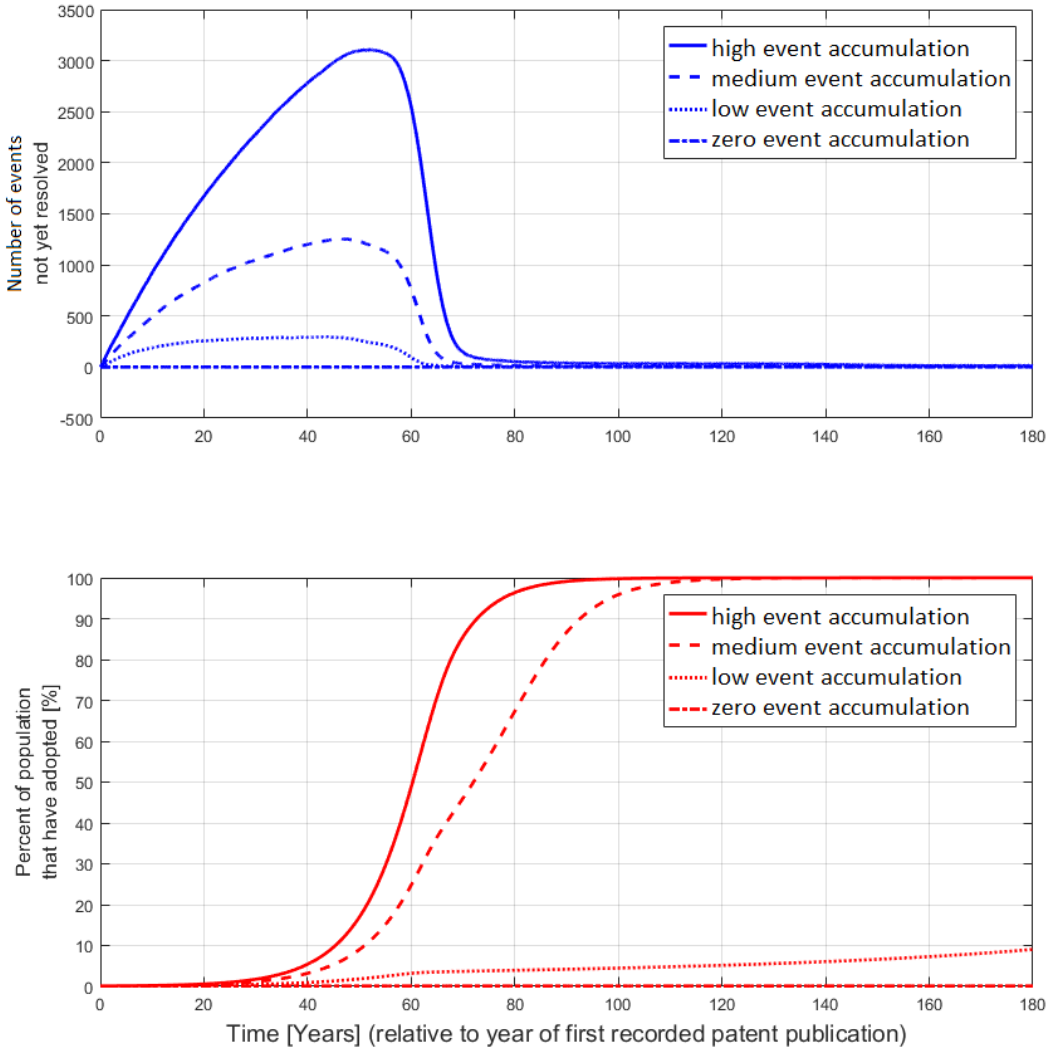


Figure 6.52: Dependency of modelled reactive substitutions on the accumulation of anomaly-related events (science and technology components of new technology set to zero)

step, based on the classification of each technology. Increasing either of these parameters leads to a greater accumulation of anomaly-related events that accelerates the technology substitution process.

To acquire a better understanding of behaviours demonstrated by the fully assembled technology substitution model, sensitivity studies for the rate of presumption and rate of adoption gains have been conducted, as shown in Figs. 6.53 and 6.54 respectively. Fig. 6.53 shows that as the rate of presumption is increased, the peak adoption rate shifts forward in time. However, the maximum adoption rate is also notably reduced. This may suggest that high levels of presumption earlier in the simulation, encouraging adoption ahead of what would otherwise be an imminent technological failure, reduces the urgency of the transition. This could be interpreted as the model reflecting a more prepared population under these circumstances, producing a slower paced substitution.

By contrast, Fig. 6.54 shows that increasing the rate of adoption gain has very little influence on the population's expected levels of presumption. Confidence in the existing technology remains high for

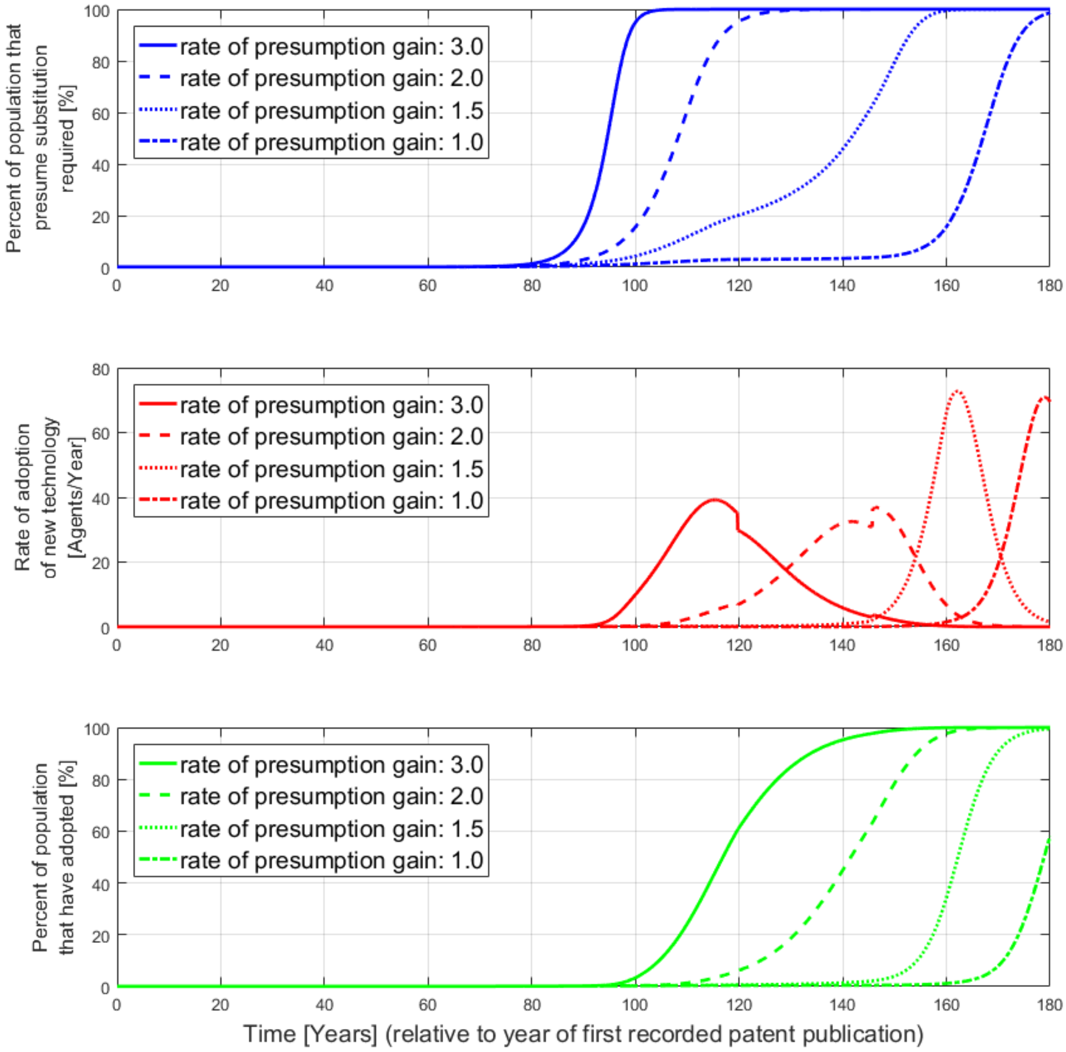


Figure 6.53: Influence of rate of presumption gain on modelled presumption and adoption behaviours

tested gain values, suggesting that the model predicts *word-of-mouth* effects (associated with the number of existing adopters) to greatly exceed levels warranted by the technological failures or new technology developments observed for more exaggerated gain values. High gain values almost represent a hysteria effect, where a population adopts based solely on a heightened dependency on current social momentum (i.e. a group thinking confirmation bias). The true level of adoption justified by new technology developments or existing technology functional-failures, is far less than takes place. This may be similar to hype surrounding certain ‘must-have’ designer products, sold as radically new technology. As such, the level of presumption does not match that of adoption until considerably later, when confidence in the previous technology gradually declines for more genuine reasons. These ‘high gain’ scenarios reflect an impulsive form of behaviour, so it is presumed that for the model to represent rational behaviour, the rate of adoption gain needs to be lowered relative to the rate of presumption gain. Additional experimentation during model building and calibration supported this conclusion, with more realistic behaviours observed when the rate of adoption was reduced relative to the rate of presumption. This is partly evident in Fig. 6.54, which shows that as the rate of adoption gain is reduced towards the lower end of the scale, development effects again become more apparent in the shape of the S-curves.

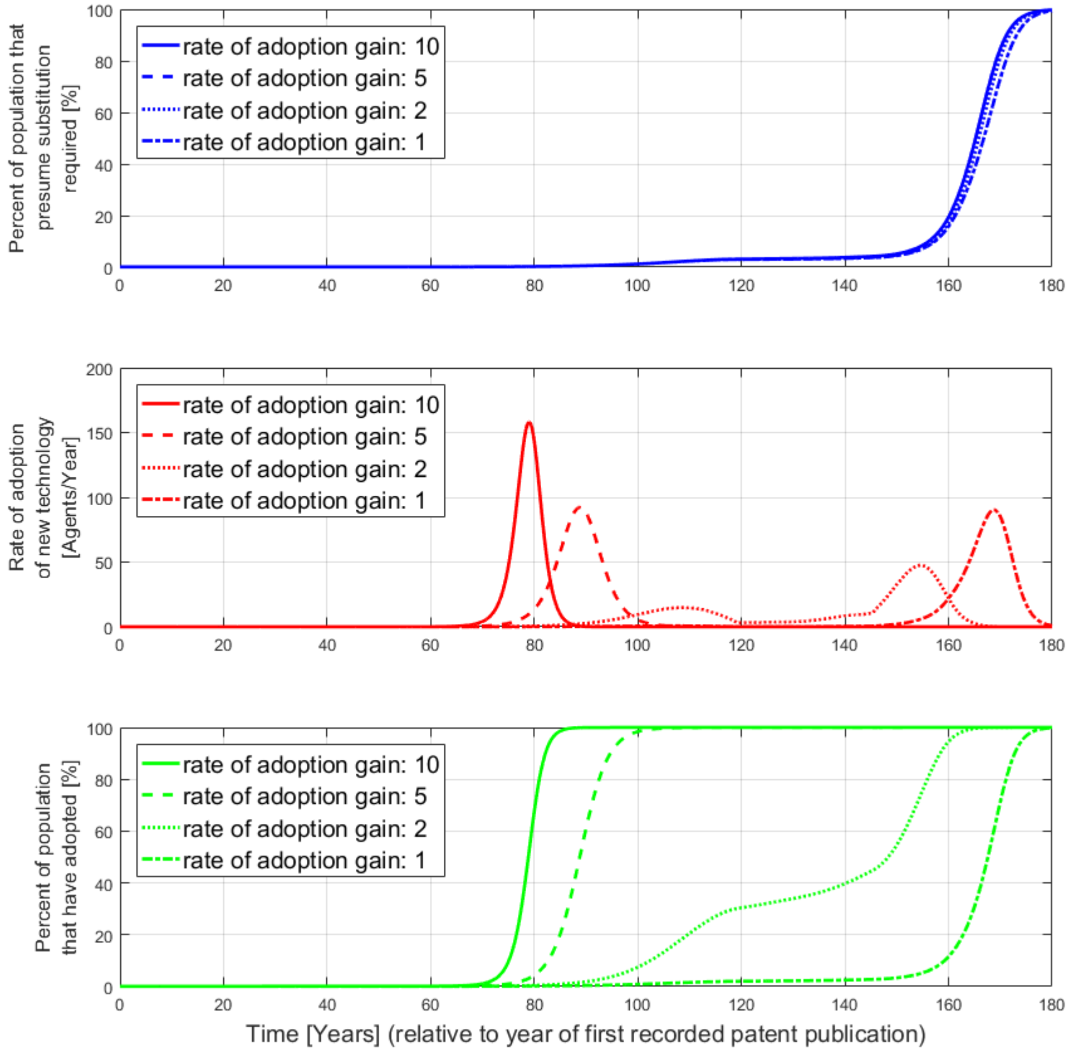


Figure 6.54: Influence of rate of adoption gain on modelled presumption and adoption behaviours

Whilst increasing the rate of presumption gain behaved as expected, the more complex behaviour illustrated by increasing the rate of adoption gain shows that careful calibration of the model is still required to avoid unintentional behaviours.

6.6 Calibration of the technology substitution model

To evaluate the technology substitution model against the 9 technologies meeting minimum data requirements, a two-stage calibration process was employed. This involved separating technologies into their two substitution groups, and calibrating the model for each mode in turn. The process is summarised in Fig. 6.55.

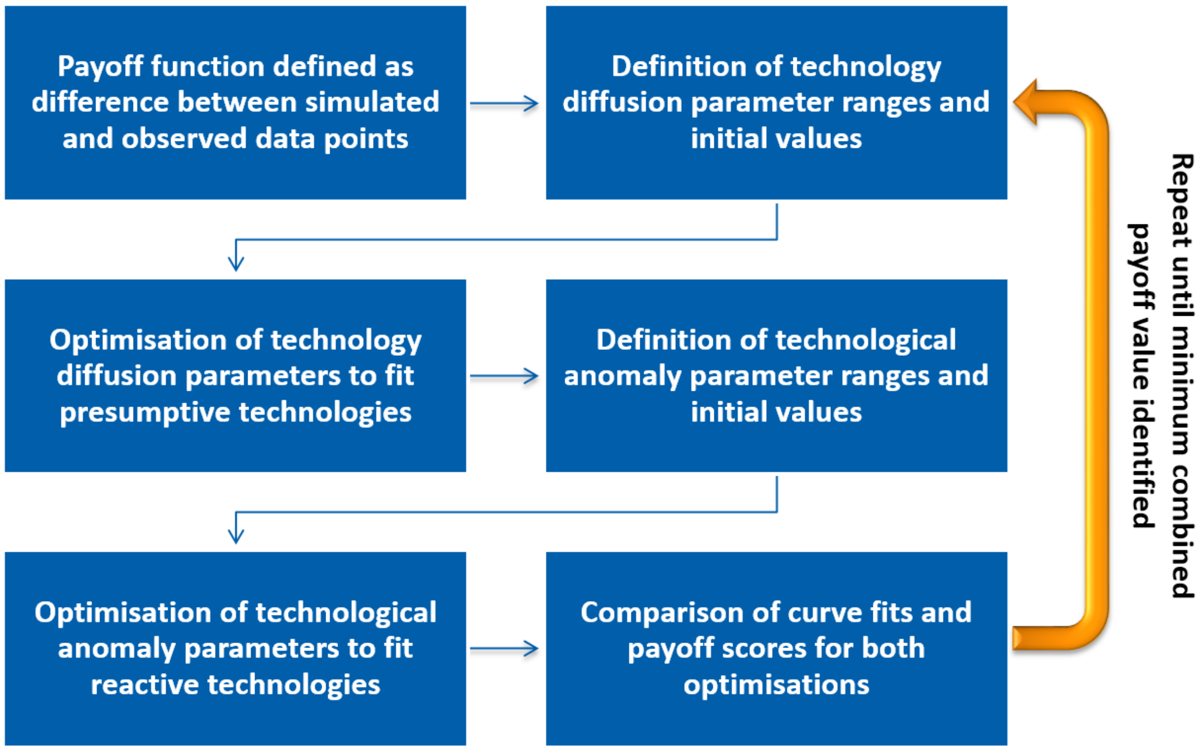


Figure 6.55: Two-stage optimisation process used in calibration

Table 6.2: Calibration parameters for technology substitution model design of experiments

Calibration set	Input parameter	Range	Increments	Initial value
Presumptive	New technology normalisation constant	0 - 2.0	0.1	1.0
	Rate of adoption gain	0 - 5.0	0.1	0.3
	Rate of presumption gain	0 - 5.0	0.1	0.5
Reactive	Anomaly normalisation constant	0 - 1000	0.5	25
	Maximum time to resolve an anomaly-related event	0 - 100	0.25	1.0
	Mean number of events observed per time step	0 - 100	0.25	0.5

Before calibration can take place, a payoff function needs to be defined to gauge the relative improvement of one set of parameter values over another. To maximise the amount of data points considered when fitting each time series, the payoff function considers any time point where historical data exists, rather than focusing on a specific feature to compare. This is necessary as in some cases, if only considering take-off points in adoption data, very few real data points may be available for comparison, which would present considerable information loss. Consequently, the payoff function is calculated by subtracting the squared error of differences between the predicted *percent of population adopting new technology* and observed *market share* values from the corresponding Integral Squared Error (ISE) term, using a binary weighting to indicate the presence of historical data [Ventana Systems, a,b]. This ensures that the payoff value is always negative, and as a result both optimisation stages attempt to maximise this towards zero. Having defined the payoff function, Table 6.2 specifies the user-defined parameters, ranges, and intervals considered in each calibration stage.

Table 6.3: Final technology substitution model parameters following calibration

Input parameter	Final value
Anomaly normalisation constant	257.5
Maximum time to resolve an anomaly-related event (presumptive mode)	1.0
Maximum time to resolve an anomaly-related event (reactive mode)	50.5
Mean number of events observed per time step (presumptive mode)	0.5
Mean number of events observed per time step (reactive mode)	75.25
New technology normalisation constant	1.0
Rate of adoption gain	0.5
Rate of presumption gain	1.0

Optimisation proceeds by considering the presumptive set of technologies initially. This set is selected for the first pass at calibration as in this condition, anomaly-related events are assumed to occur very infrequently, meaning the simulation will not be as sensitive to their effects. This allows the three calibration parameters controlling presumptive effects, which are universal to both presumptive and reactive conditions, to be refined first without too much interference from anomaly-driven components. Subsequently, anomaly-specific parameters are considered, which with the exception of the *anomaly normalisation constant*, are only significant for reactive substitutions. The ranges and initial conditions in Table 6.2 were based on conclusions from the sensitivity studies discussed in sections 6.4 and 6.5, and results from experimentation during the construction of the model. During the first stage, anomaly-specific parameters are kept at these initial conditions, whilst a grid-based design of experiments searches for the best permutation of the first three parameters. From this, a payoff score is calculated for the current optimum for presumptive technologies.

Switching to reactive technologies, parameter values defined for the *new technology normalisation constant*, *rate of adoption gain*, and *rate of presumption gain* are used, whilst running a new design of experiments for anomaly-specific parameters. In this way, a refined *anomaly normalisation constant* is determined relative to values of *maximum time to resolve an anomaly-related event* and *mean number of anomaly-related events observed per time step*. This constant is maintained when reverting to the presumptive technologies, whilst the other two anomaly-specific parameters are returned to their default values in Table 6.2 (as accumulation of anomaly-related events would not be expected for presumptive technologies).

The procedure is then restarted for the presumptive technology set with the new anomaly normalisation constant. In addition to the payoff scores for each calibration stage, the generated curve fits were also reviewed for each set of technologies, to verify if model dynamics behaved as expected. In this way, several loops through this process were made to converge on the final values shown in Table 6.3.

6.7 Results and discussion

Using the parameter values in Table 6.3, the simulation results shown in Figs. 6.56 and 6.57 were obtained for reactive and presumptive substitutions respectively.

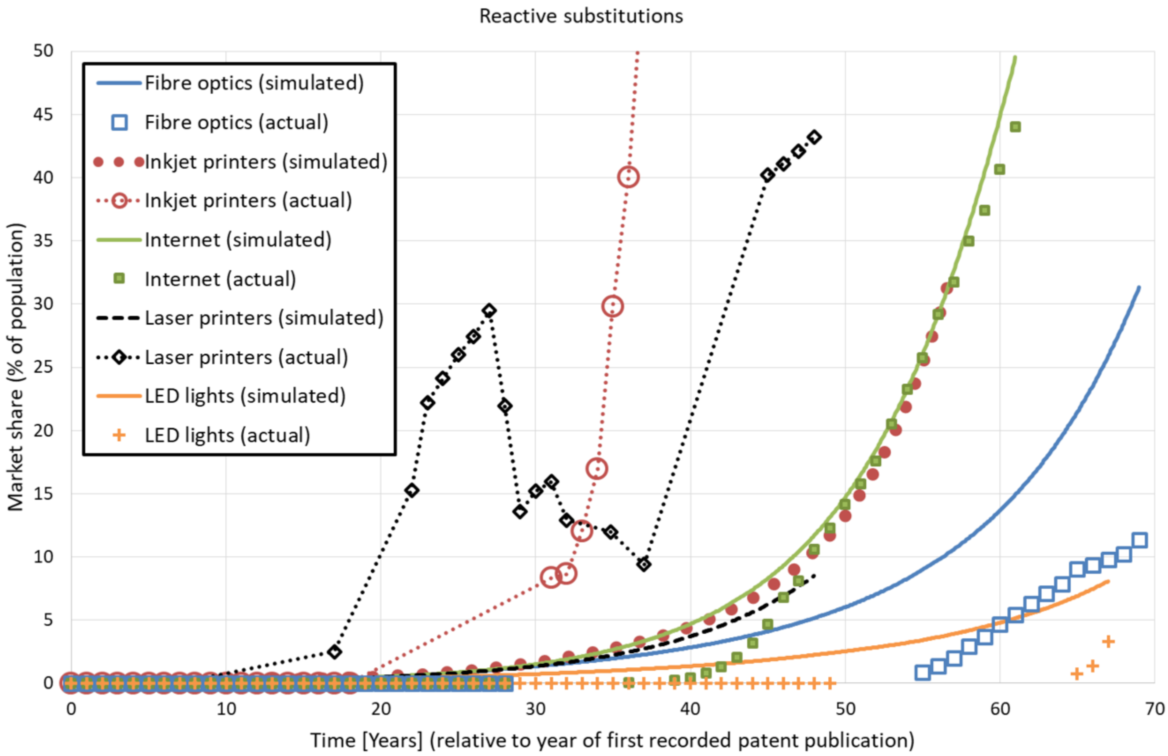


Figure 6.56: Calibration results for all reactive substitution technologies considered

Considering the reactive substitutions results first, Fig. 6.56 shows that the simulation achieves a better fit for some technologies than others. Notably inkjet and laser printers are not well fitted. This is partly due to the rapid take-off in both technologies following development (shifting towards a step function rather than an S-curve), but also the fluctuating adoption rates after take-off, which are more reflective of strong competition effects. Whilst broader socio-economic effects are thought to be captured by bibliometric input data (based on evidence provided in chapter 5), direct competition effects between specific technologies are not necessarily captured in this model. This makes more sense when considered relative to Fig. 6.3, as the sudden take-off in inkjet and laser printers closely corresponds to a rapid decline in market share of impact and dot-matrix printers. This implies that these technologies' sudden gain resulted from impact printers' equally rapid loss. Following the observations made in section 6.3, these replacement technologies may reflect the *Creative Destruction* mode of substitution [Adner and Kapoor, 2015]. It is possible that the current model may not be well adapted to handle this particular mode of substitution. However, for simplification purposes, competition effects in the current model are also limited to the substitution between an existing technology and a single new emergent technology (unlike the inkjet and laser printer scenario where multiple competing emergent technologies existed). The model also assumes a zero-sum resource competition between new and existing technologies. This last point is unrealistic as zero-sum competitions are rare occurrences, meaning this is another area where the model could be led astray. Returning to these specific examples, Fig. 6.3 shows that laser printers initially took off at a similar rate to the decline observed in impact printers. However, as inkjet printers (which took off slightly later than laser printers) rapidly eclipsed this steady commercial growth, laser printers declined, initially appearing to have missed their opportunity. This could potentially be improved upon by either accounting for competition between multiple emergent technologies explicitly in the simulation, or perhaps employing more advanced versions of the Bass diffusion model which takes more complex competition effects into account.

When considering the remaining reactive technologies, the model appears to perform slightly better, although Fig. 6.56 demonstrates for LEDs that predicted results can still struggle to capture the sharpness of observed take-offs. One way of improving this would be to increase the maximum rate of adoption, but this would result in adoption occurring much too quickly for presumptive technology substitutions. Alternatively, Sood & Tellis' observation that step functions more accurately reflect some technology performance curves [Sood and Tellis, 2005], may be applicable to some technology adoption curves. As such, the optimisation procedure presented may only achieve approximate fits here, due to the assumption that technology diffusion follows a more gradual S-shape. System dynamics can model both S-curves and step functions, so future adaptations may be possible to investigate whether optimisation based on a combination of S-curves and step functions for different substitution categories can achieve a better fit.

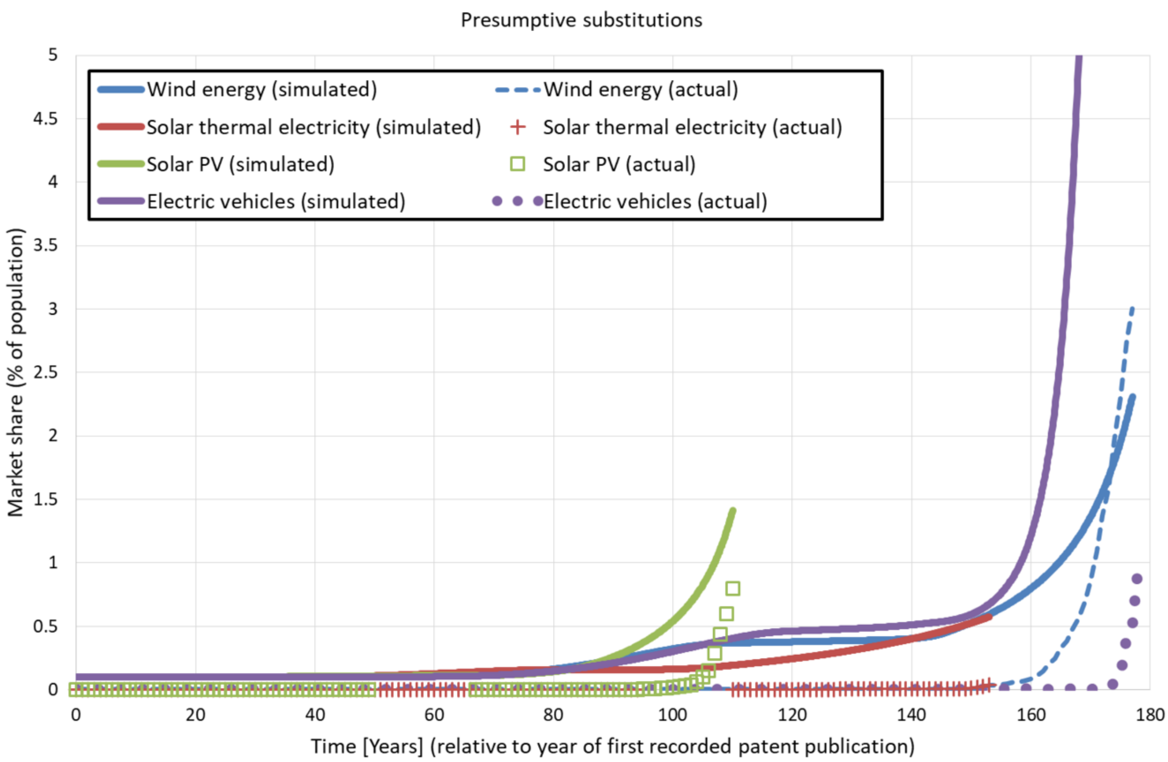


Figure 6.57: Calibration results for all presumptive substitution technologies

Table 6.4: Goodness-of-fit measures for calibrated technology substitution model

Technology	Class	R^2	Adjusted R^2	Root Mean Square Error	Mean Absolute Error
Electric vehicles	P	0.732	0.725	8.88%	3.26%
Fibre optics	R	0.966	0.964	7.14%	4.23%
Inkjet printers	R	0.340	0.302	35.43%	21.95%
Internet	R	0.986	0.986	2.03%	1.30%
Laser printers	R	0.647	0.616	18.95%	14.20%
LED lights	R	0.675	0.662	1.66%	1.02%
Solar PV	P	0.689	0.682	0.28%	0.20%
Solar thermal electricity	P	0.530	0.524	0.22%	0.19%
Wind electricity	P	0.760	0.757	0.32%	0.25%

The achieved fit for the presumptive technology set is somewhat better, as shown in Fig. 6.57, although the sharpness of take-off still proves a challenge for these technologies. However, another more minor issue becomes apparent when trying to fit the simulation to the low adoption levels of these technologies. This is a persistent offset of 0.1% from the start of the simulation for predicted technology adoption. This results from integration calculations in Vensim, which require an initial non-zero value to be specified for the *number of adopters* in the Bass diffusion model, for accumulation to occur. This was initially set to 1 (representing the first adopter of the new technology, most likely the inventor), but when taken in the context of the population size of 1,000, this represents 0.1% market share. This would not normally be an issue, except when considering technologies that have very low market shares (i.e. less than 5%), where the error is significant in proportion to final market share values. This means that the previous literature recommendation from Goldenberg et al. that 1,000 agents is sufficient to observe expected dynamics is still true [Goldenberg et al., 2001], but it may not be sufficient to guarantee accuracy for technologies where adoption remains low. Therefore, if this analysis was to be re-run it would be advisable to use a larger representative population (one order of magnitude larger should eliminate this issue), although this would slow the simulations and optimisation process. Ultimately this means that the current model still provides a reasonable explanation of dynamics in these conditions, but with further accuracy improvements still advisable.

When considering the global fit against all 9 technologies, the model appears to perform better. This can be seen from goodness-of-fit measures in Table 6.4. Reasonable R-squared and adjusted R-squared values (i.e. > 0.6) are obtained for 7 of the 9 technologies, with the exception of inkjet printers and solar thermal electricity. In the case of inkjet printers, the discrepancies in fit have been discussed relative to the reactive technologies previously. Considering the simulated values for solar thermal electricity, the poor goodness-of-fit measures observed here are caused by the 0.1% market share offset discussed above. Hence this is thought to be more of an artefact of model construction rather than a reflection of poor behavioural trends, as final adoption values are so low for this technology (representing only 0.036% of the world's electricity generation by 2014). All other historical market share values are at least an order of magnitude larger by the end of the simulation, so this error-bias is magnified for this technology. From this it could also be argued that solar thermal electricity failed to achieve commercialisation at this point in time, making it more characteristic of a *non-starter technology* (which the original classification model was not set-up to identify). However, misclassification is considered less likely here based on the very long dormant phases observed for other presumptive substitutions. In this context, solar thermal electricity is not yet the most extreme late bloomer.

In terms of the adjusted R-squared values in Table 6.4, these are generally very close to the original R-squared values. This is because only two explanatory variables are considered in the model, corresponding to the scientific and technological development efforts recorded as functional data objects respectively. It is important to note the distinction between explanatory variables and parameters. Explanatory variables, which the simulation uses but are not themselves calculated, are measured or observed inputs specific to each model application (i.e. each technology), whereas parameters are by definition constant across all applications [Brun et al., 2006]. Increasing the number of explanatory variables has two opposing effects. Firstly, it enables greater explanation of model variability, improving predictions. Secondly, the added complexity and supporting parameters now required to model the system can simultaneously increase estimation error, and therefore cause less accurate predictions [Brun et al., 2006].

Considering the global fit, the average R-squared value across all 9 technologies is 0.703, and the average adjusted R-squared value is 0.691. This means that when calibrated the substitution model explains approximately 70% of the variance observed for these technologies. This suggests that the model can explain variability in the real-world market share data to a good extent, although as more disproportionally large RMSE and MAE values suggest, this does not guarantee accurate predictions. This is perhaps unsurprising considering that the calibration aims to achieve a global optimisation set against all of the technologies, rather than separate optimisations against individual technologies. Consequently, the calibrated parameters represent the best fit when considering the full set of technologies, but better fits against individual technologies would be obtained by re-running the optimisation process solely for that technology. A range of parameter values could therefore be generated for each substitution mode instead of a single number. Limiting calibration data to only emergence stage values will also decrease accuracy of forecasts through lack of information. However, each technology's different emergence and growth stage lengths would make it difficult to ensure predictions were based on equivalent relative timescales without rigidly segmenting data in this way (otherwise risking introducing additional translation errors and consequently the validity of the model). Lastly, it is possible that forecasting accuracy could be improved by alternative payoff function definitions (such as those based on Integral Time-Weighted Error, which are more heavily weighted towards persistent errors; see chapter 4).

Therefore much scope for improvement exists in the current model. However, as only a small sample of technologies are reproduced here, the model and results are considered a proof-of-concept at this stage, and would need to be refined with additional technology datasets before being stated as definitive. This is particularly true for presumptive substitutions, as 3 of the 4 predictions are based on the energy industry, and therefore may not be representative of other industries. In any case, the small number of sample technologies does not automatically warrant a more complex model or calibration process at this stage, to avoid over-fitting the structure and parameters to the current technologies.

6.8 Conclusions from adoption pattern and system dynamics studies

Building on the statistical ranking and functional data analysis in the previous chapter, a proof-of-concept technology substitution model constructed from the two patent dimensions identified has been explored here. This model takes into account the perceived scientific and technological development efforts associated with a new technology, the accumulation of anomaly-related events for stagnating incumbent technologies, and the influences that shape the characteristics of both adoption and presumption (as described in chapter 2).

The first observation from an examination of historical market share trends in section 6.1 is that a distinction appears to exist between technologies arising as a result of technological failure, and those arising from presumptive technological leaps, confirming prior literature claims. This was illustrated in Fig. 6.8 by the disparity in take-off points for reactive and presumptive substitutions, with technologies in the latter category generally taking considerably longer to achieve market success. However, for the system dynamics model developed in this chapter, many of the technologies in Fig. 6.8 unfortunately had insufficient data to enable use in later calibration. As such, discussion and analysis beyond this point only considered 9 example technologies.

By examining the functional components for the science and technology indicators, several further observations were made. Firstly, for reactive substitutions, although led by science, the magnitude of scientific and technological development efforts tends to remain fairly well matched throughout, and typically achieves a steady level of development effort about half-way through the emergence stage. This gives the impression of technology in close pursuit of newly discovered science, potentially following a recent stagnation event. It was also noted that the scale of non-corporate assignees (representing laboratory-based technology development efforts) seems to be less significant for reactive substitutions, maybe implying that technology development is not as complex, or hindered, in its route to commercialisation as with presumptive substitutions. Examples of both *resilience illusion* and *creative destruction*, as per Adner's framework, can also potentially be seen here [Adner and Kapoor, 2015].

These observations were contrasted with those of presumptive technologies. Here it was found that, for the technologies considered, the science and technology components were much more unbalanced then their reactive counterparts. Low levels of scientific development were recorded initially (potentially due to pre-existing knowledge to draw from), in contrast to an initial surge and then reduction of technological activity, consistent with hype and disillusionment patterns [Dedehayir and Steinert, 2016, Linden and Fenn, 2003]. As such, the *number of non-corporate assignees by priority year* was taken to reflect technological maturity, complexity, or the extended scope for technical exploration. Lastly, it was observed that presumptive technologies tended to show a steady increase in scientific development throughout the emergence stage, until achieving a level similar to those seen for reactive technologies towards the end of the stage. Shortly after this, commercialisation would occur.

From the findings in sections 6.1 and 6.3, and literature evidence in chapter 2, the four sub-models constituting the overall technology substitution model were developed, in accordance with the verification criteria outlined in section 6.4. This built on earlier experimentation which indicated that normalisation of model components (representing scientific and technological development efforts towards an emerging technology) may not be well-suited to observed substitution modes when based on comparative measures against global journal and patent publications. Instead, a more consistent approach was identified, based on a standard mathematical normalisation function (described in Appendix F). Another insight gained from previous versions of the model was the need to translate potential observations of disillusionment, noted in the functional components (see section 6.3), into an active retarding influence for presumptive technologies. With the inclusion of this mechanism, the model was successfully able to reflect adoption trends observed in both reactive and presumptive substitutions. Subsequently, causal traces and sensitivity studies verified that each constituent model behaved as expected against dual-mode operating characteristics. Similarly, overall model verification was confirmed in section 6.5, following sub-model assembly and further sensitivity testing. From this, it can be attested that behaviourally the model acts as expected (with the exception of runaway social momentum in situations where the *rate of adoption gain* is set higher than the *rate of presumption gain*), and that substitution patterns follow those observed in the literature and historical data.

Calibration against real-world data revealed that the model appears to perform relatively well at a macro level, but not so well at an individual technology level. In this regard, the model was found to have the explanatory power to account for approximately 70% of the variability observed, with the remaining 30% thought to relate to competition effects and the limitations of applying S-curve approximations to step functions (although further investigation of *creative destruction* may also be valuable here). Realistically, this means that the system dynamics model is able to approximate take-offs in adoption for 7 of the 9 technologies considered when using a global, rather than individually tailored, calibration procedure. However, not tailoring optimisation to each specific technology penalises accuracy. Pinpoint accuracy is not necessarily required for decision-making purposes during conceptual stages of design, which can be based on approximate timescales (or the relative differences in technologies measured using these approximated timescales). Ideally however, further improvements should be made if continuing with the system dynamics approach. One of the easier adjustments to make, although more time consuming in computation terms, would be to increase the population size to avoid unfairly distorting the error measurements in technologies with lower market share values at the end of the simulation. Equally, simplified representations of a new technology's extension opportunity (and its impact on persuasiveness) should be further improved upon in any subsequent versions. These and other possible extensions, including considering alternative bottom-up approaches, are discussed in the next section. Ultimately though, the model, analysis, results, and discussion presented in this chapter should only be considered as indicative rather than definitive at this stage, due to the limited number of technologies evaluated.

6.9 Further extensions

In addition to the features and limitations described for the current model, a range of further extensions and improvements could be incorporated. Whilst the model already takes account of the populations' awareness of scientific and technological developments, hype and disillusionment cycles, resource dependencies, and effectiveness of communications (at least to a limited extent), there are many other influencing factors that could reinforce or reduce new technology substitution rates. These include factors related to competition, conservatism, decision-making, hierarchical structures, innovativeness, risk aversion, and technology learning curves, to name but a few (see chapter 2 for discussion of these influences). If continuing with the system dynamics approach, the work of Daim et al. provides a useful illustration of how a broader and more realistic range of socio-economic considerations and innovation attributes can be incorporated into a system dynamics representation of technology diffusion [Daim et al., 2006]. The need for more sophisticated competition effects has been mentioned in section 6.7, but the most appropriate technique to apply in this instance is left as an area for future exploration. Similarly, risk aversion is another area for possible future expansion. This is accounted for at present through the fluctuating confidence levels associated with both incumbent and emerging technologies, and the corresponding impact on the persuasiveness of the new technology. However, this does not yet fully address financial risks associated with technology substitutions, where return-on-investment criteria needs to be more robustly modelled (beyond the zero-sum resource and skills competition included). Meanwhile, the influence of hierarchical social frameworks (including group thinking biases) on the adoption of new technologies is partially accounted for in the current model by the *coefficient of innovation* parameters, *word-of-mouth* effects (where rates of presumption and/or adoption vary directly with the fraction of the population still to adopt [Niu, 2002]), and feedback loops reinforcing industries' resistance to moving away from 'normal' technology. These all lead to complex growth patterns in the rates of presumption and adoption based on the adapted form of the Bass diffusion model used. However, segregation of the population into different hierarchical layers could further exacerbate non-linear growth effects. This is based on Hughes' observation that large technological systems are structured, bureaucratic, and less adaptable [Hughes et al., 1987].

Considering the stages of evolution of LTS described by Hughes (see chapter 2 for details), it is reasonable to claim that several of these have been incorporated into the current technology substitution model. The first two stages, invention and development of the new technology, are captured by the scientific and technological development profiles extracted from patent data from the emergence stage of the TLC. The third stage, innovation, is only partially and indirectly accounted for, by the accelerating growth in resources available to new technology advocates following the emergence stage, accompanied by an expanding sphere of influence. The fourth stage, technology transfer, is represented by the links between adopters, credibility, sphere of influence, and *word-of-mouth* effects. This is in the sense that an increase in the number of adopters gives rise to improved credibility in a wider range of situations (potentially through standardisation and consensus on use), which expands the sphere of influence of the technology (potentially including a broadened ability to set new standards in the future). However, this is not an explicit reflection of technology transfer between domains. Stage five, growth, is captured by the non-linear diffusion of adopters predicted by the Bass diffusion model, which accelerates significantly past a critical adoption threshold, and is accompanied by further increases in confidence, credibility, and influence. The sixth stage, competition, is again only partially accounted for by a simplified representation of resource dependency and resurgence in development of an incumbent technology following the exposure of technological anomalies. Lastly, the seventh stage, consolidation, is only indirectly modelled through the plateauing of adopters once the population has fully converted to the new technology. Consequently, from this brief review, it can be said that stages 1, 2, and 5 of Hughes' framework are explicitly addressed in the model, whilst stages 3, 4, 6, and 7 provide a good indication of directions to consider in future extensions.

In many cases, the additional factors that could be included (e.g. measures of conservatism, innovativeness, user adaptability, etc.) relate to a common theme of individuality in adoption processes and decision-making. As such, probably the single largest limitation of the current approach is the use of aggregate-level methods (i.e. representing a population as a single continuous entity) to model decisions that are ultimately taken on an individual level. This means that the behavioural measures in the simulation (e.g. confidence, credibility, persuasiveness, power, etc.) reflect the average levels assumed across the population, rather than the full spectrum of behaviours that individuals or communities demonstrate. In this respect, the current model does not capture the real-life idiosyncrasies that add further variability to adoption patterns. As shown in chapter 2, diffusion models based on bottom-up approaches have successfully enabled some of these extremes of behaviour to be incorporated into wider population representations, giving rise to emergent behaviours similar to those noted in real-life. However, as technological stagnation and substitution modes were the specific focus here, it was considered necessary to examine these first globally to a) identify if there was any basis to the categorisation suggested by the literature, and b) generate baseline assumptions and simulations that more complex bottom-up analysis can be compared against. In this regard, the model has achieved its main purpose by showing that the signature behaviours expected for these higher level modes of substitution can be reproduced using only the relevant extracted patent data and classification category (derived from the same patent data), prior to moving on to this next stage of bottom-up analysis.

Chapter 7

Conclusions, discussion, and recommendations for future work

Expanding on previous accounts of technological substitutions, the purpose of this study was to build a capability to detect and reproduce historically observed patterns in transitions between technologies, and to test the hypothesis that technology substitutions, following one of two principal modes, can be recognised from analysis of patent data. This capability was intended to form part of a wider product and technology lifecycle management toolset, enabling performance expectations and anticipated market responses of dissimilar technology options to be evaluated during conceptual design. These two substitution modes were expected to relate to significantly different adoption characteristics, corresponding to either presumptive or reactive behaviours. More specifically, scientific foresight and performance stagnation are believed to play crucial roles in sparking presumptive innovations and reactive transitions respectively. In both cases, technological anomalies are believed to arise, resulting from either scientific or technological crisis, which trigger eventual shifts to the next commercially prevalent technology. It was speculated at the outset that it would be possible to recognise these principal modes of substitution from patterns emerging in technology datasets, and that drivers used to determine the mode associated with a technology would provide insight into the expected rate of adoption. To investigate this hypothesis, the study posed the questions *'what does a technological substitution look like?'* and *'to what extent are technological substitution dynamics dependent on scientific foresight?'*. These questions were subsequently addressed through a combination of historical narrative, and a coupling of existing technology forecasting techniques with bibliometric analysis of patent data.

7.1 Conclusions

In response to the first question, the diffusion of innovations across large technological systems (LTS) was initially considered (question 1A). In this field of study, performance development and market adoption of new technologies have both conventionally been represented by S-curve growth models inspired by biological systems, as discussed in chapter 2. These are based on ideas of technologies achieving a critical mass which subsequently leads to non-linear development and adoption behaviours (i.e. take-off). This reflects chronicled observations that a small number of successful backers with sufficient influence and power can sway large portions of the population, stimulating more widespread growth. Another founding assumption of many S-curve performance models is that eventually, all technologies arrive at a limiting condition based on physical constraints, defining the upper bound of the S-curve. In parallel, observations of large technological systems by Thomas Hughes and others suggested that innovations often move between seven stages of evolution corresponding to *invention*, *development*, *innovation*, *technology transfer*, *growth*, *competition*, and *consolidation*. This appears to occur in a non-sequential and backtracking fashion. As technologies pass through these phases within hierarchically structured systems, recognition of performance gaps between adopters and non-adopters in adjoining sub-systems accelerates both development and market adoption. The rate of diffusion can also be greatly amplified in situations such as telecommunications, where the value of the new technology increases as more adopters share the same platform (termed *network externalities* in innovation diffusion literature). In relation to more revolutionary technological substitutions that lead to the emergence of General Purpose Technologies, these transitions signal a shift from *normal science* and *normal technology* to more radical approaches, and from *puzzle solving* to a *puzzle definition* mode of development. In these instances, system expansion is initially shaped by goals of the specific creative groups behind the innovation, but as growth progresses, whole new industries and complementary technologies may be spawned from the diffusion process, if supported by sufficient skills and resources.

Next, the general characteristics of technological substitutions were explored (question 1B). Here, the framework proposed by Adner was discussed, which characterises four types of technological substitution based on typically observed market adoption patterns. These correspond to notions of *creative destruction*, *robust coexistence*, *resilience illusion*, and *robust resilience* (as described in chapter 2) depending on the *emergence challenges* facing new technologies and *extension opportunities* available to existing technologies. By describing technology substitutions in terms of high and low scenarios for these two dimensions, it is possible to anticipate likely market dynamics, based on the degree of overlap in performance expectations between technologies (question 1C). The fastest of these substitution modes, *creative destruction*, occurs when emergence of the new technology is unhindered, leading to the rapid downfall and replacement of an already weakened existing technology. At the other end of the spectrum, *robust coexistence* describes a prolonged period of market coexistence, during which both technologies steadily improve and compete. In *resilience illusion*, emergence challenges are high, although set against low extension opportunities for the existing technology. This allows incumbent technologies to appear dominant in the market for a prolonged duration, until a sudden transition when the new technology overcomes previous development hurdles. Lastly, *robust resilience* occurs when the existing technology continually outpaces development of the emerging one, giving the impression of a new technology that is ultimately over-hyped.

Generalising these modes further to only consider the extension opportunity dimension, these lower level modes can be grouped into *presumptive* and *reactive* substitutions, depending on whether extension opportunities carry the incumbent technology past the new technology's point of emergence. These groupings are consistent with the ideas of *presumptive anomaly* and *functional-failure* developed by Edward Constant, discussed in chapter 2. Presumptive and reactive modes therefore describe transitions that take place over a prolonged or reduced duration respectively, once a new technology first emerges. Drawing from existing literature evidence, 23 technologies were categorised in chapter 2 in accordance with Constant's model of technological change and these two principal substitution modes. The distinction between these modes was quantified to some extent in chapter 6 from an examination of market adoption data for these technologies, revealing that reactive technologies tend to achieve commercialisation and significant market uptake typically at least twice as fast as presumptive technologies.

To address the second research question, assumptions behind conventional S-curve models were re-examined. In reality, technology development has been observed to stall for a range of economic, social, and technical reasons, whilst empirical studies suggest it may never truly be possible to say that a technology has failed. Consequently, beyond the assumed physical limit defining the top of the S-curve, additional definitions of *technological failure* are required to explain historical observations of substitutions occurring following periods of both temporary and more sustained technical stagnation (illustrated further in the performance data and timelines in chapters 2 and 5). Three such definitions were provided by Graeme Gooday relating to 1) social marginalisation from a range of cultural and societal influences, 2) humanity's ever-increasing performance expectations, and 3) the divergence of opinions that means a technology may be a failure in some people's eyes, but not others. Only the second, relating to functional-failure, depends on scientific foresight. In this condition, Constant argued that quantifiable evidence must be present to persuade market users that the existing technology has 'failed'. From a technology development perspective, this evidence relates to performance metrics and measures of scientific and technological progress (question 2A). Whilst performance metrics for any technology are dependent on its field, measures of scientific and technological progress are more generalisable from bibliometric and patent analysis techniques. Considering the latter, the most common format for describing *technological progress* follows a Technology Life Cycle patent assessment, which measures a technology's development relative to its competitive impact and progress in transitioning from product to process-based innovation. Measures of science are also typically found to reflect either *scientific activity*, *production*, or *progress*, with contributions to technical knowledge (as might be derived from citation analysis) being the most common indicator of *scientific progress*. The bibliometric measures of *scientific production* in this study reflect both contributions to knowledge of scientific activities, and wider socio-technical influences that are relevant for adoption models.

In accordance with these measures, cross-examination of patent data trends against historical timelines in chapter 5 illustrated how the development potential of the technologies considered was dependent on a range of scientific, technological, and socio-economic factors. However, system dynamics modelling in chapter 6 implied that without the inclusion of scientific foresight (and its derived influence on presumption), significant differences to predicted adoption timings arise when substitutions are solely reliant on functional-failures. A review of the patent indicator metrics corresponding to the *number of cited references* and *number of non-corporate patent assignees by year* derived in chapters 5 and 6, and identified as providing the best representations of scientific and technological development efforts respectively, provided further indications of the dependency on scientific foresight. Reactive substitutions within the technologies appeared to show more closely matched levels of scientific and technological development efforts than presumptive cases, with steady levels of development in both domains usually appearing around half-way through the emergence stage. However, science led technological development efforts in these instances. This was in contrast to the low levels of scientific development recorded initially and the unbalanced relationship between scientific and technological developments for the presumptive technologies during the emergence phase. Commercialisation of the presumptive technologies often occurred soon after scientific development efforts neared the more steady-state development levels observed for reactive technologies. Another notable difference in the technologies was that development patterns associated with the *number of non-corporate patent assignees by year* for the two modes appeared less important in reactive substitutions. Conversely, presumptive technologies experienced a surge of technical activity earlier in the emergence period, prior to more concentrated scientific efforts substantially later.

Examining relationships between technological substitutions and scientific foresight in more detail, characteristics of technological anomalies, based on the ideas of Constant, were explored in chapter 2 (question 2B). Constant described technological anomalies appearing (represented by 'events associated with an anomaly' in this study), related to either more frequent conditions of functional-failure, or less frequent presumptive insights into future technology performance. The latter type of anomaly prescribes the eventual failure of the existing technology, based solely on scientific insight, before any functional-failure or framework exists that supports the anomaly. However, Constant noted that without a quantifiable alternative technology, technological anomalies of any kind can be dismissed as a limiting condition to the normal technology. If such an alternative does exist, anomalies can cause a technological crisis, potentially leading to substitution or technological revolution (question 2C).

Hughes meanwhile noted that in technological subsystems where progress is being held back compared to other sub-systems (termed as *reverse salients*), innovation efforts are concentrated to resolve these performance gaps and enable the full potential of the current technology. If a reverse salient cannot be resolved with the current technology, highlighting an observable functional-failure, it can support more radical frameworks and presumptive anomalies. Whilst the market share trends in chapter 6 provide a means to quantify differences in presumptive and reactive adoption modes, the system dynamics model enables the influence of presumptive anomalies and performance stagnation on technological substitutions to be examined in greater depth. This model, based on literature evidence, assumed that if events associated with functional-failure anomalies accumulate slowly, adoption remains at low levels, in contrast to situations where functional-failure events accumulate rapidly.

In terms of the viability of the data-driven substitution model constructed (question 2D), this builds on existing literature findings and successful demonstrations of coupling bibliometric measures with system dynamics modelling for technology forecasting (outlined in chapter 2). These previous studies indicated strong links between technology performance, credibility, availability of skills and resources, the effectiveness of communications, hierarchical social structures, economic success and technology adoption. Aspects of each of these dimensions were included in the model, as described in chapter 6.

However, examining first the technology classification model's viability as a basis for the substitution model, results in chapter 5 show that functional linear regression was able to correctly identify 19 out of 20 substitution modes considered from data pertaining to the emergence stage, based on derived measures of scientific and technological development. Additionally, the technology classification model performed consistently well in statistical ranking of predictive capability when considering multiple goodness-of-fit measures, whilst permutation testing suggested the regression fit is based on specifics of individual technologies, and is not occurring by chance. These findings suggest that automated statistical analysis of patent indicator time series may provide a means of classifying technological substitutions. Further, preliminary evidence suggests that classification can be achieved based on partial time series, through segmentation of datasets relative to identified Technology Life Cycle features. Regarding the technology substitution model, testing of the system dynamics framework in chapter 6 showed that behaviourally the data-driven models are viable, being able to reproduce substitution patterns observed in literature and historical data, although with limited accuracy that may restrict usefulness at the current fidelity. More precisely, at a macro level the model performed satisfactorily (approximating take-offs in 7 of the 9 technologies), with explanatory power to account for approximately 70% of the observed variability, albeit whilst suffering more at an individual technology level.

Consequently, it is possible to conclude that the theorised modes of substitution based on scientific foresight and performance stagnation, corresponding to presumptive and reactive adoption behaviours respectively, are a reasonable means of classifying technology adoption profiles. Specifically, substitution modes for the case studies considered were found to be identifiable from derived scientific and technological development effort metrics, whilst a proof-of-concept substitution model gauged the impact of each mode on adoption behaviours using a stochastic representation of functional-failure.

7.2 Discussion

This study has contributed to the existing literature on technological substitutions by demonstrating that a combination of bibliometric, pattern recognition, statistical, and causal procedures can be applied to identify likely modes of substitution in conceptual stages of design. This enables modal impacts on expected adoption trends to be tested. The resulting classification model demonstrates robust predictive capabilities for the technologies considered, supporting the literature-based substitution categorisation, and providing evidence suggesting substitution modes can be recognised through automated processing of patent data. The analysis also indicates that the functional data analysis and statistical ranking exercises in chapter 5 are in good agreement. Building on this, the system dynamics model of technology substitution behaves as expected and enables scientific and technological development efforts to be mapped relative to measures of functional-failure and adoption trends, although is more limited in its immediate applicability. The use of partially complete datasets (i.e. segmented time series) in both the classification and diffusion modelling stages of this analysis may though enable future extensions to real-time applications. However, the existing ability to identify and test the sensitivity of substitution modes relative to observed adoption characteristics could still be of interest to research and development organisations, or strategic decision-makers, by reducing the uncertainty in technology selection processes during conceptual design. This could lead to reductions in the time-to-market for new products and services, and allow robust product and service strategies to be developed in response to continually evolving demographic, economic, and physical environments.

Many new insights have been explored in formulating these models. First amongst these is the notion of technological failure. Historical narratives show the importance of understanding the type and cause of failure being observed, and that both social and technical issues are likely to contribute to the stagnation of technological development. Without considering these aspects it is difficult to determine if the full potential of a technology has actually been reached. To identify instances where presumptive leaps inspired substitutions, chapter 2 noted that a modelling framework would need to identify if a functional-failure already exists, and if new scientific discoveries have preceded any such failure. As such, the modelling framework needs to consider scientific and technological development efforts in both new and existing technologies. An examination of development data provided insight into the emergence challenges (or degree of exploration required in the *puzzle definition* phase) linked to the new technology, accumulation of events related to functional-failure anomalies, and consequently the perceived extension opportunity for the incumbent technology. These assumptions imply that for model validation, it would be expected to see presumption of a substitution to a new technology arise from either scientific or technological development trends in patent data. However, adoption resulting from presumption would only be expected in situations where the population is aware of the new science, relative extension opportunity of the existing technology, and availability of alternative technological solutions. For example, insights gained from the science of compressible fluid dynamics and knowledge of sound barrier limits highlighted the curbed extension opportunity of piston-engined aircraft to Frank Whittle, whilst patents emerging in power station combustion systems offered a potential alternative. When no presumption is present, adoption still occurs, but resulting instead from the accumulation of events (representing issues, obstacles, or challenges) associated with a technological anomaly. This follows the assumption that perceptions of scientific and technological progress do not equate alone for the tendency to adopt. Accordingly, the technology classification and substitution models developed were demonstrated to be consistent with basic model validation criteria in chapters 5 and 6.

Additional insights appear from an inspection in chapter 6 of the patent indicators identified statistically as providing the best predictive capability. Metrics derived from patent data suggested here that reactive substitutions experience accelerated uptake and a much steeper rate of adoption than presumptive technologies following take-off. This may result from recognition of technological stagnation in the incumbent technology, and as such, perhaps reflects the urgency of demand in reactive conditions, although this could also reflect quicker learning curves associated with reactive replacements. Similarly, measures of *number of non-corporate patent assignees by year* may indicate technological maturity, complexity, or the extended scope provided for technical exploration. This can be inferred from its previously established association with laboratory-based technology development efforts. Such efforts appear to be less significant for reactive substitutions, which may reflect replacements using simpler innovations than presented by presumptive concepts, or technologies rushed from lab to market due to the urgency of replacement. The latter premise is perhaps supported by observations that technological development appears to closely follow science in these cases, giving the impression of being hot on its heels. This was potentially illustrated by the rapid switch to multiple core microprocessors after cooling challenges became significant in the early 2000s to the point that a maximum practical clock rate was felt to have been reached from the continual miniaturisation of circuit boards and transistors. In contrast, the early surge then slump of lab-based development recorded by this metric for presumptive technologies may be consistent with literature evidence of hype and disillusionment patterns, as discussed in chapter 6. In parallel, the relative imbalance observed for presumptive technologies between scientific and technological development efforts during the earliest stages of emergence may result from pre-existing scientific knowledge.

Considering more broadly the validity of this study, several steps have been taken to ensure the research conforms to expected standards. Firstly, method and data sources have been systematically structured and refined based on problem structuring techniques and known method limitations (detailed in chapters 3 and 4). This enabled a bounded research programme within the time available. Validation themes linked to different computational forecasting techniques were identified and ranked in chapter 4, informing modelling and simulation requirements that needed to be satisfied to demonstrate credible findings. These included general prerequisites for credibility to all audiences, such as methodological rigour, evidence of traceability, elaborating the researcher's subjectivity, and exploring human factors that may or may not have influenced model development. Equally, this analysis identified specific occupational expectations that must be satisfied for model credibility. From a commercial perspective, these include the informativeness of predictions and defining market areas most likely to be impacted by technological substitutions, alongside academic requirements of minimising systemic and random forecasting errors. As a result, statistical approaches were combined with causal exploration in chapter 6 to allow a fuller examination of technology-specific influences that may shape adoption behaviours. Extracted datasets were also reviewed in detail in chapters 5 and 6, suggesting that the bibliometric indicators used capture many observed socio-economic events in addition to technical advances. From this it was concluded that there was a risk of double-accounting if additional socio-economic measures representing the same events were included in the substitution model. Similarly, results were cross-checked against historical development trends and adoption curves (see chapters 5 and 6), using appropriate statistical and goodness-of-fit measures to demonstrate the practicality of the models (see chapter 4). This included calibrating the final technology substitution model against extracted historical datasets, using well-established optimisation control measures. One specific risk identified in chapter 3 for this study's exploratory approach to data analysis is ensuring that results can be shown to be reliable and generalisable, which often requires repeating simulations numerous times to identify patterns at higher levels of abstraction. Consequently, cross-validation and permutation procedures were applied where possible to minimise the risk of poor out-of-sample predictions, although this should be further verified by testing additional case studies (see chapters 3, 4, 5, and 6 for details). Furthermore, sensitivity studies in chapter 6 confirm that sensible behavioural effects, conforming to real-world expectations, occur when testing dual-mode operating characteristics, accumulation of events associated with anomalies, diffusivity parameters, and resource assumptions.

7.3 Limitations of the research and future directions

In relation to the limits of this research, it was acknowledged in chapter 3 that the author's background predisposes him towards more quantitative than qualitative approaches, and that in adopting an exploratory analysis rather than seeking to refute an existing theory, there is a risk of missing undocumented influences. To address risks of subjectivity, a systematic approach was applied using problem structuring methods such as situation mapping, *CATWOE*, *Purposeful Activity Systems*, and *Hierarchical Process Modelling*. Nevertheless, basic human fallibility means that the resulting research questions, boundaries, and activities will not have been perfectly defined, although it is hoped the risk of errors has been sufficiently reduced through these methods. Beyond this, it is necessary to consider features identified from prior research that have not been addressed here, and limitations specific to the data and modelling techniques used, giving rise to future research directions.

A review of previous literature regarding technology substitutions was presented in chapter 2. Whilst many model features were based on these findings (detailed in chapters 5 and 6), there is scope for improvement and expansion. In the context of large technological systems, this includes coupling the scientific, technological, and functional-failure substitution features in the existing models with more direct representations of:

1. the innovation, technology transfer, competition, and consolidation stages of LTS, which are currently only accounted for indirectly (see chapter 6 and [Hughes et al., 1987])
2. competition between multiple emerging technologies (see chapter 6)
3. financial and labour dependencies shaping risk aversion beyond a zero-sum resource and skills representation (see chapter 6)
4. the resurgence of existing technologies [Constant, 1973, Rogers et al., 2005]
5. diffusion through heterogeneous populations and disjointed networks [Chatterjee and Eliashberg, 1990, Dattée and Weil, 2007, Goldenberg et al., 2001]
6. the hierarchically structured and bureaucratic nature of LTS [Hughes et al., 1987, Mäkinen et al., 2013]
7. technology learning curves (i.e. skill based technological disruptions that require training and resources to enable effective uptake) [Rogers et al., 2005, Chatterjee and Eliashberg, 1990, Dattée and Weil, 2007, Andolfatto and Smith, 2001]
8. global preferences for incremental versus more disruptive technology developments [Andolfatto and Smith, 2001]

Additionally, a shift from aggregate to individually-focused models of adoption behaviours is recommended as a natural extension. Such models are better suited to capturing emergence and decision-making processes [Rogers et al., 2005, Chatterjee and Eliashberg, 1990, Peres et al., 2010]. This involves translating the concepts demonstrated here into a suitable bottom-up modelling framework, such as agent-based approaches, and verifying consistency with the current findings. It would then be possible to add features to test the impact of individuals' idiosyncratic behaviour (as noted from previous studies) on diffusion trends under different modes. This could include studies on the relationship between the likelihood of making presumptive leaps of foresight and an individual's:

1. decision-making logic [Peres et al., 2010, Chatterjee and Eliashberg, 1990]
2. varying levels of commitment to conventional technologies [Constant, 1973]
3. scientific awareness, domain experience, and confirmation biases [Constant, 1973]
4. adherence to social norms [Constant, 1973]
5. social background [Dattée and Weil, 2007]
6. levels of innovativeness and conservatism [Peres et al., 2010, Rogers et al., 2005, Hughes et al., 1987, Constant, 1973]

Such studies would provide a means to gauge the relative importance of these factors in different types of substitution, but would require more detailed adopter characteristics and data than used in this analysis. Additionally, whilst this study provides a means to identify higher-level modes of substitution and test their impact on the take-off point in adoption, the results do not describe the eventual likelihood of market dominance. Investigations into correlations between substitution modes and probable market outcome are therefore left for further exploration, as these would require more full-length life cycle datasets than obtained here. Equally, classification into the precise sub-modes described by Adner has not been attempted, but could be if additional market and performance data was compiled for a sufficiently large number of technologies.

Considering data limitations, market and patent records have provided the primary sources of data in this analysis. Although patent metrics are usually deemed a reasonable reflection of technological development efforts, they may not directly equate to intangible metrics such as consumer confidence and credibility. This is similarly true of market data. It is likely that combining the analysis techniques applied here with further qualitative assessments would provide additional verification and a more refined understanding of the socio-technical parameters in the substitution model. For example, coupling the trend-based analysis of structured patent data presented here with qualitative analysis of the unstructured content could provide valuable insights into the *extension opportunities*, *emergence challenges*, and *reverse salients* shaping the technological landscape. Equally, this could provide a means to assess the novelty and impact of the patents being considered, and improve the relevance of patent search strategies. Advances in content-based mapping, supported by machine learning classifiers, are thought to be key potential enablers here. Likewise, patent databases are not the only means of measuring scientific and technological development, as records of industrial investments and academic publications can also present alternative perspectives on historical events. Even within the patent dimensions considered orthogonality of patent indicators relative to one another has not been ruled out. However, the risk of covariance is thought to be minimised by using only two patent dimensions in the classification model that appear to be distinct, based on an examination of the functional components in chapter 6, and which are consistent with the technological anomaly arguments described in chapter 2. Perhaps the most apparent risk with patent data is the sheer variability of results from simple search strategies and existence of multiple independent databases, although this was mitigated to some extent through the clearly defined search strategy in chapter 5. In any event, it is improbable to retrieve every patent associated with a technology due to inconsistencies in semantic search patterns, whilst off-topic records can still appear from mislabelling data entries. There are also likely to be overlaps in patent searches due to the fuzzy boundaries between closely related technologies. For example, technologies developed in steam turbines were crucial for the later development of gas turbines.

Conversely, the availability of market and performance data is sporadic, making verification of findings more problematic. For this reason, technologies have typically been labelled using a single performance metric, meaning that scope remains for additional verification and validation of the assigned substitution categories. This particular risk was addressed by detailed historical reviews of each technology's development timeline to confirm the labelling conclusions. Using only a single performance measure does, however, avoid the risks associated with attempting to combine metrics. Similarly, only a relatively small number of technologies has been considered in this study, due to the time-consuming process required for data extraction, preparation, and gathering of evidence to support labelling. This means that the results may provide a better fit to the industries directly assessed rather than more generalisable industrial applications. Therefore the results from the technology substitution model in chapter 6 should only be considered as indicative and a proof-of-concept at this stage due to the limited number of technologies considered. Further calibration against a more diverse spread of technologies is recommended to verify that the current model is not over-fitted.

Lastly, in terms of specific limitations related to modelling techniques, the dependency on large quantities of data is also linked to the first major challenge encountered. Automated data processing stages are required to extract, clean, and segment large volumes of patent records affiliated with a given technology so that sufficient material is available to ensure robustness in later pattern recognition stages. This risks over-dependency on tool automation and a lack of transparency or intuitiveness, as much of the model derivation and execution is hidden behind a screen of automation. Considerable attention was therefore paid to cleaning the data, feature extraction procedures (including cross-checks in alternative software packages), and verifying all codes generated, although as before these elements remain susceptible to human error. By calibrating model results against historical events, it was demonstrated in chapter 6 that the substitution model was able to account for approximately 70% of observed variability. The remaining 30% of variability that is not captured may arise from competition effects and limitations in applying S-curve approximations to step functions that are not directly addressed in the model. Equally, simplified representations of a new technology's extension opportunity (and its impact on persuasiveness) should be further improved upon in any subsequent versions. It is also worth noting that the calibration is based on a global, rather than individually tailored, optimisation procedure. Consequently, it is likely that technology-specific optimisations, producing a range of parameter values for a given substitution type (rather than a single global value), would provide an improved predictive capability. However, the largest method limitation probably relates to using aggregate-level models, that represent a population as a single continuous entity, to model decisions that are ultimately taken on an individual level. As a result, the model cannot (in its current form) be claimed to reproduce the real-life idiosyncrasies that add much variability to adoption patterns, and that enable extremes of behaviour to be incorporated into representations of the wider population. The classification and substitution models do, however, enable the expected higher-level modes of substitution to be detected and reproduced from limited structured patent data. In this sense, the research has achieved its main purpose in providing a foundation for future decision-making applications within Airbus' conceptual design communities. Ultimately, technology forecasting will always be a crystal-ball gazing exercise, but if a greater understanding of the mechanisms behind these transitions helps to build more robust technological systems, than society may see the benefits, and we may get to where we want to be, sooner rather than later.

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Appendices

Appendix A - Technology timelines

Table A1: Timeline of display technology
[Hanna et al., 2015, Bellis, 2017, AITpro, 2010, Genova, 2013, Walden, 2018, Tannas, 2012]

Year	Event	Major event
1855	German, Heinrich Geissler invents the Geissler tube. Created using his mercury pump this was the first practical evacuated (of air) vacuum tube, which was later modified by Sir William Crookes.	X
1859	German mathematician and physicist, Julius Plucker first identifies and experiments with cathode rays.	X
1872	Joseph May discovers that selenium's conductivity is enhanced by light.	X
1878	Englishmen, Sir William Crookes was the first person to confirm the existence of cathode rays by displaying them, with his invention of the Crookes tube, a crude prototype for all future cathode ray tubes.	X
1878	Mr. Senleq proposes FAX transmission using a selenium scanner and telegraphy.	
1880	First articles appear in Scientific American about the possibility of television.	X
1884	The first electromechanical television (i.e. television scanning disk) was proposed and patented by Paul Julius Gottlieb Nipkow. Nipkow never built a working model of the electromechanical television.	X
1888	Liquid Crystals were accidentally discovered by Friedrich Reinitzer. Liquid crystals were a scientific curiosity for about 80 years before they were used to build liquid crystal displays (LCD).	X
1890s	Victorian Trade Card predicts a device that can transmit picture and sound.	
1897	The Birth of CRT: Karl Ferdinand Braun, a Nobel-prize winning German physicist and inventor, builds the first CRT (Cathode-Ray Tube) oscilloscope, which consists of a vacuum tube that can produce images via electron beams hitting a phosphorescent surface. The technology will later be used to display images on early televisions and computer monitors. The Braun Tube was also the forerunner of radar tubes.	X
1900	First known use of the word "television" at 1900 Paris Exhibition	

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Table A1 – continued from previous page

Year	Event	Major event
1907	Discovery of Electroluminescence: British radio researcher Henry Joseph Round discovers electroluminescence, a natural phenomena that serves as the foundation upon which LED technology will later be built.	X
1907	Russian scientist Boris Rosing (who worked with Vladimir Kosma Zworykin) uses a CRT in the receiver of a television system that at the camera end made use of mirror-drum scanning. Rosing is the first to transmit crude geometrical patterns onto a television screen using CRT.	X
1908	Campbell Swinton proposes CRT for both scanning and receiving.	X
1911	Rosing and college student Vladimir Kosma Zworykin (as assistant), achieve first transmission of images.	X
1911	Swinton describes CRT system in detail.	X
1919	RCA becomes subsidiary of GE. A 28 year old David Sarnoff is named manager.	
1921	Philo T. Farnsworth, at age 14, envisages electronic TV scanning whilst ploughing hay.	
1922	C. Francis Jenkins transmits still pictures by wireless with a mechanical system.	X
1922	Farnsworth explains his electronic TV system to his high school teacher.	
1923	As a Westinghouse employee, Zworykin files a patent application for an all-electronic television system. He is not able to build or demonstrate it at this time.	X
1923	Ernst Alexanderson starts television work at GE.	
1924	Kenjiro Takayanagi starts his television work in Japan.	
1925-28	Glimpses of TV's Capabilities: John Logie Baird, a Scottish engineer, demonstrates some of the capabilities of television including transmitting recognisable human faces (1925), moving objects (1926) and colour (1928).	X
1925	Baird demonstrates his mechanical system at Selfridge's Store in London	X
1925	Jenkins transmits "moving objects" – (a windmill) in Washington, D.C.	X
1925	Zworykin demonstrates a working system to his bosses at Westinghouse.	X
1925	Baird builds the world's first working television system. The world's first working television system was electromechanical.	X
1926	Baird gets his first licence to transmit television in London.	X
1926	Farnsworth receives a $6000 advance from George Everson in Salt Lake City.	
1926	Philo Farnsworth marries Elma Gardner, and moves to San Francisco.	
1926	Alexanderson is proclaimed the "Inventor of Television" by the press in St. Louis.	
1927	January - Alexanderson demonstrates mechanical TV to Radio Engineers.	X
1927	September - Farnsworth transmits a straight line via his electronic CRT system.	X
1928	Baird transmits from London to New York, using his mechanical system.	X
1928	Takayanagi gives a demonstration of his CRT system in Japan.	
1928	Farnsworth demonstrates his CRT system to the press in San Francisco.	X
1928	Station WLEX, Lexington, Massachusetts, (about 15 miles NW of Boston) begins broadcasting via mechanical system.	

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Table A1 – continued from previous page

Year	Event	Major event
1928	The world's first successful colour transmission by John Logie Baird. The colour transmission was made using an electromechanical television system.	X
1928	The first working electronic television (all-electronic) is built by Farnsworth. The all-electronic television system did not use or have the motor-generator that was used in the electromechanical television systems.	X
1929	Zworykin begins development of the kinescope, his CRT receiver.	
1929	April 1929 – W1WX (which would eventually become W1XAV), the Shortwave and Television mechanical station, goes on the air.	X
1930	January - David Sarnoff becomes President of RCA at age 38.	
1931	Allen B. Du Mont made the first commercially practical and durable CRT for television.	X
1935	Patent interference between Zworykin and Farnsworth ruled in favour of Farnsworth. Prevents RCA from gaining total patent control of television.	
1935	Sarnoff evicts Armstrong from the Empire State building and announces million dollar research and testing plans for television.	
1935	March - Germany begins what they call the "first television broadcasting service in the world". This is low resolution and has few receivers.	X
1936	April - First RCA demonstration in 4 years of all-electronic system, 343 lines, 30 frames per second.	X
1936	Farnsworth also broadcasting 343-30 at Wyndmoor, Pennsylvania station.	
1936	Summer – Berlin Olympics televised by Telefunken and Fernseh, using RCA and Farnsworth equipment, respectively.	X
1936	Autumn – Farnsworths travel to England to help Baird in his competition with EMI.	X
1936	November 2 – BBC begins two-year Baird-EMI competition, broadcasting analog TV from Alexandra Palace. It is hailed as the "world's first, public, regular, high-definition TV station".	X
1936	November 30 – Fire destroys Baird labs at Crystal Palace	
1937	February – BBC declares EMI the victor in the competition.	X
1937	The coronation of King George VI and the Wimbledon tennis tournament are televised in England. Nine thousand sets are sold in London.	X
1937	France orders the world's most powerful transmitter to be constructed in the Eiffel Tower.	
1937	18 Experimental Television Stations are operating in the United States.	
1938	June – RCA announces the Image Iconoscope, a camera tube that is almost ten times more sensitive to light than the earlier Iconoscope.	X
1938	October – Sarnoff announces that RCA will begin regular broadcasting at the World's Fair	
1939	The first electronic CRT television set (DuMont model 180) was introduced to the US market, available at a cost of approximately 125 dollars (Saperecom 2015)	X
1939	March 31 – Farnsworth begins operations at Fort Wayne, Indiana	

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Table A1 – continued from previous page

Year	Event	Major event
1939	April 20 – Sarnoff announces from the New York World's Fair that "Now we have added sight to sound". Ten days later, at the opening ceremonies, FDR is the first president to be televised, TV sets go on sale the following day.	
1939	Approximately twenty-thousand electronic sets operating in England.	
1939	1 September 1939 – UK-television transmissions switched off due to imminent outbreak of war.	X
1939	October 2 – Farnsworth signs patent-licensing agreement with RCA. This is the first time that RCA ever agrees to pay royalties to another company since it was founded in 1919.	
1940	FCC announced September 1st start date for commercial television, but cancelled that decision when RCA began advertising early.	
1940	FCC formed a special committee, called the NTSC (National Television Standards Committee), to decide on industry standards. There were 23 experimental television broadcasting stations operating in the United States.	
1940	June: Both RCA and Philco televised the Republican convention, held in Philadelphia	
1940	August: A young (33) Peter Goldmark announced to the NTSC that CBS had marketable colour television.	X
1941	March: The NTSC announced the recommended USA standard of 525 lines and 30 fps (frames per second). FCC announced that commercial broadcasting could begin July 1st.	X
1941	July 1st: NBC was the first broadcaster with commercially sponsored broadcasts – CBS, DuMont and others followed in the Autumn	X
1941	December 7th: Pearl Harbor	X
1942-45	All commercial production of television equipment is banned in the U.S. for the rest of the war. NBC's commercial TV schedule is cancelled. Limited broadcasting does continue, however, throughout the war years, in a few cities, for a few hours per week.	X
1946	CBS gave the FCC a demonstration of their mechanical colour system. Viewers were impressed.	X
1946	John Logie Baird, Scottish television pioneer, dies.	
1946	Post war production of American TV sets begins	X
1946	1946 7" Viewtone - the first post war American television (utilising a pre-war design), marketed as a 1946 model, but sold in very small quantities starting in August 1945. The selling price was $100. The president of Viewtone, Mr. Irving Kane, wanted to tap into the post war television market as quickly as possible, and also wanted to offer a set that people could afford. Eventually four different models were sold, all using Du Mont picture tubes. The company went out of business in August 1947.	
1946	1946 7" RCA 621TS - RCA announced both the 621TS (and the 630TS) to the American public on October 7th 1946. RCA then had a five city (newspaper) advertising campaign for both sets, with sales beginning in November 1946.	

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Table A1 – continued from previous page

Year	Event	Major event
1946	The cabinet of the 621TS (offered in mahogany, walnut and blonde wood) was designed in the pre-war period by John Vassos, however the chassis was a post-war design. Initial price was $226.4. The 621 was on the market very briefly and was quickly outsold by the 630TS with a 10" screen. Production was 17000 units - not many have survived until today - the set is popular among collectors.	
1946	1946 10" RCA Model 630TS - Initial selling price was $352.0. It weighed 95 lbs. and was on the market from 1946 until 1949. Many other manufacturers bought the 630 chassis, and had their own cabinets made. Even in 1950, the set was offered in kit form and a hobbyist could build a do-it-yourself TV set. Approximately 43000 were sold the first year and hundreds-of-thousands continued to be sold in later years. Collectors call this the Model-T of television, and it is the first set completely designed and marketed post war.	X
1947	RCA flooded the market with black & white sets to slow the potential launch of CBS colour. An adapter (about $100) would have to be installed to all non-CBS colour sets. The FCC ruled CBS colour is 'premature'.	X
1947-1950s	In 1947, the Soviet Union releases the film Bwana Devil and bills it as "the first feature length motion picture in 3-dimension natural vision". In total, between 1952 and 1955, there are 46 3D movies released, including the famous House of Wax. Poor visual quality was off-putting to viewers, and the 3D craze did not catch on until decades later.	
1948	Pye Television, a UK firm, set up a demonstration at the Australian "Royal Easter Show", held in Sydney, six years ahead of the first Australian public broadcasts. This was the first time TV was demonstrated in Australia.	
1949	Facing the colour challenge head-on, Sarnoff ordered stepped-up development of an all-electronic RCA colour system. Perfected system is ready by December 1950.	
1949	Farnsworth Radio and Television is sold to ITT. Philo Farnsworth, at age 43, suffering from alcoholism, is no longer a part of the television industry.	
Early 1950s	Colour Television: Television begins to incorporate colour, encoding both luminance and chrominance for the first time. Since TVs, which at this time in the U.S. encode programs using the NTSC (National Television System Committee) System, vary from model to model, colour changes based on viewers' equipment. This leads to the nickname "Never The Same Color" to describe the NTSC technology.	X
1950	CBS presents colour television system using a spinning mechanical colour wheel. In October, the FCC approves CBS colour for commercial broadcasting. Sarnoff orders his "holy crusade" at RCA to perfect electronic colour television.	X
1951	The share of US households with a TV passes the 20% threshold	
1951	June 25th: CBS broadcasts a one-hour Ed Sullivan show, but only two dozen CBS sets can receive the colour broadcast. By the end of June, RCA demonstrates its electronic colour system, and the industry takes notice.	X

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Year	Event	Major event
1951	October: All colour TV production is suspended for the duration of the Korean conflict.	X
1951	December 6th: Code of Practices for Television Broadcasters is adopted in the USA. Also known as the "Seal of Good Practice".	
1952	Début of Curved TV Screen: The Cinerama is unveiled as the first curved television screen in a handful of movie theatres. The technology is based on the science behind human vision, and it becomes a tourist attraction that people travel miles to see. The trend of curved screens will not hit the consumer TV market for more than half a century.	X
1953	March 25th: CBS gives victory to RCA in U.S. colour TV war.	X
1953	December 17th: FCC approves electronic RCA colour system, reversing its prior decision to accept CBS mechanical system. It calls this new RCA colour system "NTSC" colour.	X
1954	RCA places its first all-electronic colour set on the market early in the year, the CTC-100, with a 12-1/2" screen, for $1000. Sales were predicted to be 75000 units – however, only a reported 5000 were sold. The real number is thought to be closer to 1000 sets sold to the public. Many sets were donated to schools and also sold at a discount to employees.	
1956	Time magazine calls colour TV "the most resounding industrial flop of 1956"	X
1961-62	Invention of LED: In 1961, Robert Baird and Gary Pittman patent an infrared LED (light-emitting diode) – the first LED – for Texas Instruments. It is, however, invisible to the human eye. The next year, Nick Holonyack invents the first light LED that's visible to the human eye and becomes known as "the father of the LED".	X
1962	Discovery of the Williams Domain in LC material, Sarnoff Labs	X
1964	The first working liquid crystal display (LCD) was built by George H. Heilmeier. The original LCD displays were based on what is called dynamic scattering mode (DSM). LCD technology makes flat-screen television possible, and later LCD research by James Fergason, an American inventor, leads to the first modern LCD watch in 1972.	X
1964	The first flat plasma display panel (PDP) was invented by Donald Bitzer, Gene Slottow and Robert Willson. Plasma TVs, however, do not become widely successful (or possible) until the advent of digital technologies years later.	X
1964	The Japan Broadcasting Corporation (NHK) begins experimenting with high-definition television after the 1964 Tokyo Olympics.	X
1965	Touchscreen Technology: E.A. Johnson develops what some consider to be the world's first "touch screen" technology. At first, it is used for air traffic control, but after sometime, around 1995, it becomes the predecessor to the screens used in today's ATMs and ticketing kiosks.	X
1967	Birth of IMAX: The inception of IMAX occurs when Canadian film-makers band together in Montreal to produce a multi-screen film installation – the first truly large-screen film experience – by syncing together nine film projectors.	X
1971	Invention of the twisted-nematic mode of LCDs	Label 1

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Table A1 – continued from previous page

Year	Event	Major event
1972	Synthesis of cyanobiphenyl LC material at Hull University	Label 1
1972	The first active-matrix liquid crystal display (LCD) panel was produced by Westinghouse.	Label 1
1974	Panasonic designs a TV prototype that can display 1125 lines of pixels (about 2.5 times that of standard definition).	X
1977	The first true all LED flat panel television TV screen was developed by J. P. Mitchell.	X
1980s and 1990s	Rise of Large-Scale TVs: Consumer televisions continue to get larger and larger. Rear projection televisions are the standard – though they take up a great deal of space – until about 2005, when they are replaced by lighter and slimmer technologies like Digital Light Processing (DLP), Liquid Crystal on Silicon (LCoS), and improved Plasma and LCD.	
1980s and 1990s	Touchscreen Invades: IBM, Microsoft, Apple, HP and Atari are among just a few of the tech companies bringing touchscreen into the mainstream in this era. In 1992, IBM's Simon is the first phone with a touchscreen. FingerWorks, a gesture recognition company that is later acquired by Apple, produces a line of multi-touch products in 1998.	
1982	Seiko introduces the world's first LCD TV watch.	
1982	The first mass-produced pocket television was the Sony Watchman FD-210. The Sony Watchman was also the first flat CRT television in production.	
1984	First Macintosh Computer: The first Mac becomes available to the consumer market, with a 9-inch, monochrome 512×342 pixel display. Mac's as of 2015 with Retina 5K have a 5120x2880 pixel display – this represents an increase of about 8400% – that supports millions of colours.	X
1987	OLED: Researchers at Eastman Kodak invent OLED (organic light-emitting diode) technology; chemists Ching W. Tang and Steven Van Slyke are the primary inventors.	X
1988	The Sharp Corporation develops the world's first 14-inch colour TFT LCD TV. The LCD TV model was called the Crystaltron.	Label 2
1990s	Full Colour Plasma Display: Plasma displays continue to improve in resolution with technology brands debuting new and improved models throughout the '80s and '90s. Plasma technologies continue to evolve into the 2000s, particularly for large-sized screens (40 inches and above), until they are eventually surpassed by LCD.	
1995	Larger Than Life LED: The Fremont Street Experience, the world's largest LED display at the time, is put on display in Las Vegas. It measures over 1500 feet long and 90 feet high.	
1996	The first public digital high-definition television (HDTV or HD) broadcast in the United States. The official US public launch of the HDTV digital broadcasting system is technically considered to be 1998. **HD ready refers to the abilities of television receivers to display high-definition pictures.*	Label 3

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Year	Event	Major event
1998	Launch of HDTV in the U.S: The official public launch of HDTV digital broadcasting system in the United States takes place. Though high-definition technology has been in the works (primarily in Japan and other countries) for years, it does not become mainstream in America until the late 1990s.	Label 3
c. 2007	Sometime around 2007, LCD televisions surpass Plasma in popularity due to their large size and lower cost. LED technologies also continue to improve, and LED-backlit LCD televisions become commonplace. OLED technologies also continue to improve, and can function without backlight.	Label 4
2007	Touchscreen is the Status Quo: The 2007 iPhone is the first commercially successful smartphone that is exclusively touchscreen, though there is debate about which tech company lays claim to the "first" touchscreen smartphone. Touchscreen becomes the industry standard for mobile devices from this point forward.	X
2008	The world's largest Plasma TV is a 150 inch Plasma TV made by Panasonic, standing 6 ft high and 11 ft wide.	
2009	The world's largest LED high-definition video display screen in the world is the Mitsubishi Diamond Vision display at the Dallas Cowboys Stadium. The LED HD display measures 160 ft wide and 72 ft high and is nicknamed the "JerryTron" after Cowboys owner Jerry Jones.	
2010	The world's largest Plasma 3D TV is a 152 inch Plasma TV made by Panasonic	
2010s	Electronic Paper: Though e-paper technology was actually pioneered in the 1970s, it became popularity in e-readers and other devices in the 2010s. E-paper is portable, reusable and can be "erased" – or re-written on – thousands of times.	X
2010	The world's first 3D LED HDTV released by Samsung (Samsung 3D LED 7000). Announced in February, 2010. LG announced the release of their first 3D LED HDTV, the LG LX9500 in March, 2010.	X
2013	Quantum-Dot Technology: Quantum-dot technology arrived on the scene in 2013 with debuts by LG, but the display tech is quickly picking up speed. QD is an advanced version of an LED-backlit LCD TV, providing exceptional image quality and vivid hues.	Label 5
2014	Apple begins to market its products – for the first time in 2014 – with "Retina Display" and later "Retina HD" Display. The selling point is that the resolution of the screen has reached the point that the human eye is incapable of determining any pixelation at all. Retina Display is a term used exclusively with iPads, iPhones, iPods, Macs and MacBooks.	
2015	AMOLED: AMOLED, or active-matrix organic light-emitting diode, increases screen resolution and quality of OLED screens. Today, versions of AMOLED include Super AMOLED, HD Super AMOLED, Super AMOLED Advanced and more – the labelling generally varies based on tech companies' marketing terms.	X

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Year	Event	Major event
2015	Mainstream Resurgence of 3D: 3D becomes popular in the movie theatres and at home, due to improved technologies such as alternate-frame sequencing (battery-powered glasses for 3D viewing at home) and autostereoscopic technologies (3D that does not require glasses).	X
2015	High resolutions continue to improve – not only on televisions, but on mobile devices and wearable technologies. Along with higher resolutions come larger televisions. In 2004, the average TV was a CRT of just 27 inches, and today's screens often measure 60 inches or more.	
2015	Televisions are getting thinner and more flexible – e.g. a Sony 4K TV that is 4mm thick at its thinnest point, which debuted at CES 2015. In addition, flexible OLED and AMOLED screens are in the midst of penetrating the market, and companies are competing for the first fully bendable smartphone screen.	
2015	While curved screens on televisions are becoming increasingly popular, CES 2015 saw curved screens on more than just TVs, including the Samsung ATIV One 7 Curved, an all-in-one computer with a curved monitor.	
2015	While 4K was a main theme of CES 2014, 5K was debuted at CES 2015. 4K, also referred to as 4K2K, means that a device has a horizontal resolution of at least 4000 pixels.	
2015	Improved 3D and Virtual Reality: Displays are allowing for increasing user interactivity, such as the HP Zvr Virtual Reality Display, a monitor that debuted at CES 2015 that allows users to manipulate 3D images on the screen.	

Table A2: Timeline of electric vehicles
[Handy, 2014, Shahan, 2015, Watts, 2017, Thompson, 2017]

Year	Event	Major event
1821	Michael Faraday creates the first weak experimental electromagnet	
1828	Hungarian inventor Ányos Jedlik, who had invented an early electric motor, builds a small, model car powered by this motor.	X
1831	Joseph Henry, a maths professor in Albany NY, builds the first electric motor in his quest to understand electro-magnetism. It is modelled along the lines of the "walking beam" used on early steam engines and resembles an electric teeter-totter.	
1832-39	Scottish inventor Robert Anderson invents the first crude electric carriage powered by non-rechargeable primary cells.	Label 1
1834	Inspired by reading of Joseph Henry's efforts blacksmith Thomas Davenport and his wife Emily develop the first rotary direct current electric motor and build a miniature electric railcar running in a circle on a tabletop; it is not strong enough to carry the weight of its own battery. The Davenports use silk from Emily's wedding dress as wiring. His invention failed to interest investors. This might have been due to a lack of imagination among his audience, but practical minded people would point out the dependency on relatively expensive single use batteries, as neither practical rechargeable batteries, nor distributed electric power are available. He creates a proof of concept, which is generally ignored until after the Civil War.	Label 1
1835	In the Netherlands, Professor Sibrandus Stratingh of Groningen and his assistant, Christopher Becker, build a small electric car powered by primary cells (non-rechargeable batteries).	
1837	Thomas & Emily Davenport, and colleague Orange Smalley, receive the first American patent for an electric machine/motor.	Label 1
1837 & 1841	Large-scale "electric cars" are finally built by chemist Robert Davidson of Aberdeen. Powered by galvanic cells, the larger one, built in 1841, can pull 6 tons at 4 miles per hour for about 1½ miles. It weighs 7 tons. Sadly, it is soon destroyed by railway workers who see it as a potential threat to their livelihood (even though electric cars were still far from economical, with the cost of using zinc in a battery being about 40 times higher than the cost of burning coal in a firebox).	Label 1
1851	The US Senate funds a prototype electric locomotive, which made a test run from Washington DC to Baltimore MD, a distance of about 40 miles (64 km). Charles Grafton Page, a US patent examiner, designs it and uses his Washington connections to get funding. The motor was like an electric steam engine with a solenoid and iron mass rather than a cylinder and piston. The effort fails when the clay separators in the primary battery cells crack and the solenoid coils overheat and short out as the insulation fails. Steam remains more practical for large-scale power at this point.	
1854	Wilhelm J. Sinsteden invents the rechargeable, lead, sulphuric acid, and lead-oxide battery	

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Table A2 – continued from previous page

Year	Event	Major event
1859	French physicist Gaston Planté improves the lead acid cell to the point of commercial viability with telegraph system use in mind and invents the rechargeable lead-acid storage battery. The original Planté design had smooth, untreated lead plates separated by parchment paper and felt. They had to be cycled (recharged) many times before building up a sufficient peroxide coating on the positive plate to develop full useful capacity. Lead-acid batteries are still used in some electric cars as of 2015, and are used in gas-powered cars to help start the engines. However, most modern electric cars use lithium-ion batteries. The lead-acid batteries used to start cars are still very similar to what Gaston created.	
1869	Zenobe-Theophile Gramme patents the first practical dynamo in Paris.	
1876	Nikolaus August Otto patents a practical four-stroke engine, designed for stationary use, in Germany. The engine is made to run with help from his engineer Gottlieb Daimler.	X
1880	January 17th: Thomas Alva Edison is awarded a carbon-filament vacuum tube light bulb patent. This incandescent light becomes popular over the next three decades as the lamps become more affordable. The commercial generation and distribution of electricity for lighting, and light rail, built the necessary infrastructure for electric cars. Edison had to fight for clear patent rights, and eventually the strongest plaintiffs merged to become General Electric.	Label 2
1881	Camille Alphonse Faure, in France, and Charles F. Brush, in the US, independently come up with the idea of using a lead oxide paste to increase the capacity of the original 1859 Planté battery by a threefold capacity, greatly increasing the potential for battery traction vehicles, if the paste would stay on the plates. This leads to industrial-scale production of lead-acid batteries.	Label 2
1881	An electric tricycle built by Gaston Planté is displayed at the International Exhibition of Electricity in Paris.	Label 2
1881	Parisian engineer and carriage builder Charles Jeantaud, with the help of Camille Alphonse Faure, builds a battery electric vehicle using a Tilbury-style buggy, a Gramme motor, and the Fulmen battery. Over the next twelve years, he continued to modify this platform, installing a British motor in 1887, and a Swiss motor with a tubular plate battery built by Tonate Thommasi in 1893.	Label 2
1881	Englishmen William Ayrton & John Perry build an electric tricycle, the first vehicle to use electric lights. It uses lead acid cells, has a range of 10 to 25 miles, and has a maximum speed of 9 mph.	Label 2
1883	The Brighton Electric Railway, engineered by Magnus Volk, opens in England. The route is only a quarter of a mile long at first. This is the first commercial electric tram.	

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Table A2 – continued from previous page

Year	Event	Major event
1884	English inventor Thomas Parker builds first practical production electric car in London. He uses "high-capacity" rechargeable batteries that he designed. (Parker also electrified the London Underground, was responsible for overhead tramways in Liverpool and Birmingham, and has other such accomplishments to his name)	Label 2
1884	College drop-out Andrew Riker, while living in his parents' basement, develops an electric trike using lead-sulphuric acid batteries that has 25 miles of range.	Label 2
1886	N. S. Possons has an electric tricycle built for the Brush Electric Co of Cleveland Ohio. It has a Swan incandescent electric headlight and features the Brush Company's rechargeable battery powering a Brush motor.	
1886	Frank Sprague invents a high torque DC traction motor. It is capable of consistent speed under varying loads and does not create sparks.	
1887	Sprague uses his DC motor in the first commercial electric tram systems in North America, beginning with Richmond Virginia.	
1888	German engineer Andreas Flocken builds the first four-wheeled electric car.	
1888	Andrew Riker forms the Riker Electric Vehicle Company, which is based in Elizabeth Port, New Jersey.	
1888	Philip Pratt demonstrates an electric tricycle built for him by Fred M. Kimball of Fred M. Kimball Company. Despite Riker's (lesser known) electric trike being built a few years earlier, many say that Pratt's electric trike is the first in the US, and Pratt is often given the title, "father of the American electric automobile".	
1888	Elwell-Parker Company and rivals merge in England to form the Electric Construction Corporation. The Electric Construction Corporation thus gains a monopoly on the production of electric cars in the coming decade.	
1890-91	The first American electric car is built by William Morrison of Des Moines, Iowa. The 6-passenger wagon can travel up to 23 km/h (14 mph). The car may also be the first land vehicle steered with a wheel. Morrison, a chemist, moved to Iowa from Scotland in 1880.	X
1893	The World's Columbian Exposition is held in Chicago IL, ushering in the electrical age for most Americans. There are several motor vehicles on stationary display including an electric taxicab designed by Walter Bersey and a few German petrol vehicles. The Morrison car, now owned by the American Battery Co, is the only one moving about. It becomes well known as it is used to drive important visitors - including many future automobile manufacturers - around the grounds.	
1894	Louis Antoine Krieger begins building electric "horseless carriages" in Paris. They use regenerative braking, with the captured energy stored in a battery and later used to help power the motor.	

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Table A2 – continued from previous page

Year	Event	Major event
1894	Mechanical engineer Henry G. Morris and chemist Pedro G. Salom build the first "successful" electric car. With backgrounds in the dwindling battery tram market, Morris and Salom design and commission a heavy four-wheel electric wagon, the "Electrobat", like a small battery tram. It has a top speed of 15 mph and uses a lead acid battery. It goes into production the following year, 1895.	Label 3
1895	Morris & Salom come up with an elegant new design, which they call the Electrobat II. It is lighter weight and has front wheel drive with coil spring suspension at the rear wheels. Along with the Morrison electric it is entered in America's first automobile race, which is held in Chicago. Neither car has the battery capacity to go the distance in the freezing weather, and the race is won by the Duryea brothers, followed by some German Benz based cars.	Label 3
1896	The same Electrobat II, and a new electric built by Andrew Riker, soundly defeat five next generation Duryeas in a series of five mile sprints on a dirt horse-track in fair weather. The short range allows for a light, hot battery. Because of the high initial cost and vicissitudes of lead battery management Morris and Salom felt the vehicles are more appropriate for fleet service than individual ownership, and design an electric version of the popular horse drawn Hansom cabs for the streets of major American cities.	Label 3
1896	The first car dealer is set up in the US. It only sells electric vehicles.	Label 3
1896	Morris and Salom build a 2-seat "Electric Road Wagon" and form the "Electric Carriage and Wagon Company", apparently the first electric car company in the US. Developed as coupés and hansoms for New York City taxis, the Electric Road Wagons each have rear-wheel steering, two 1/2 hp motors, 44 lead-acid cells, and a range of 30 miles.	Label 3
1896	To overcome range limitations and lack of charging infrastructure, a battery exchange (aka battery swap) service is proposed. Implemented by Hartford Electric Light Company, the service is initially available for electric trucks.	Label 3

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Table A2 – continued from previous page

Year	Event	Major event
1897	Major commercial implementation: Samuel's Electric Carriage and Wagon Company cabs in New York, based on the Electrobat II, are the first in commercial operation. The event is announced in January - with only two cabs ready - but due to licensing delays operation actually begins in March. They soon had a small fleet of 12 Hansom cabs and one Brougham (Coupé). Venture capital for the Electrobat projects came from owners of the Electric Storage Battery Company of Philadelphia under the leadership of Isaac L. Rice. ESB is founded to provide battery sets for trams where a trolley line is not practical, to extend service past the reach of electrical lines, and where overhead wires are restricted by ordinance. They are also used for power station backup, railway lighting, and such. On the 13th of May a Columbia Mark III, the first electric car for sale to the general public, is demonstrated to the press and public. Made by a subsidiary of Albert A. Pope's bicycle empire the company has a significant advantage over the Morris & Salom New York cab start-up as they already had a factory for manufacturing the chassis and running gear, whilst the bodies were farmed out to the New Haven Carriage Co. As such The Pope Manufacturing Company of Connecticut becomes the first large-scale American electric automobile manufacturer. Although a Bersey cab prototype has been around since 1893 it takes several years to find the capital and change laws to put them on the streets of London. On August 19th, 1897 Walter Bersey's cab is finally put into service in London. The Bersey cabs use a 3½ HP Lundell motor, ran at 9 miles per hour for about 20-30 miles on a charge, and feature quick-change battery boxes. The enterprise failed in August of 1899. Painted yellow and black they were popularly called "hummingbirds" due to the bright colour and whir of the straight cut gears.	Label 3
1897	September: Isaac Rice takes over the New York cab company as the Electric Vehicle Company.	
1897	The first car to be built with power steering is an electric car.	
1898	Dr. Ferdinand Porsche, 23 years old, builds his first car, the Lohner Electric Chaise. It has a hub motor at each driving wheel and is reportedly the first front-wheel-drive car in the world.	
1898	Count Gaston de Chasseloup-Laubat of Paris sets the first known speed record in a car, going faster than any human before at 39.24 mph (62.8 km/h) in his electric Jeantaud. This earns him the nickname "Electric Count". Incidentally, the world record lasts for just a few days before being beaten by another electric vehicle.	
1899	Walter C. Baker founded the Baker Motor Vehicle Company. Thomas Alva Edison, who does not drive, buys the second one made.	

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Table A2 – continued from previous page

Year	Event	Major event
1899	Believing that electricity will run autos in the future, Thomas Alva Edison begins his mission to create a long-lasting, powerful battery for commercial automobiles. Though his research yields some improvements to the alkaline battery, he ultimately abandons his quest a decade later.	
1899	Camille Jenatzy and Count Gaston de Chasseloup-Laubat trade speed records several times throughout the year, ending in Camille Jenatzy breaking the 100 km/h (62 mph) speed barrier in an electric vehicle. He reaches a top speed of 105.88 km/h (65.79 mph). Jenatzy's vehicle is named La Jamais Contente ("The Never Satisfied").	
1899	MIT electrical & mechanical engineering graduate Clinton Edgar Woods incorporates Woods Motor Vehicle Company, 3 years after forming American Electric Vehicle Company, which then became Waverly Company.	
1899	The Baker Electric, the first production electric car, is born. It is produced by Baker Motor Vehicle Company.	Label 3
1899-1905	Ferdinand Porsche designs electric and Hybrid cars for Austrian coachbuilder Jacob Lohner & Co. The vehicles from 1900 on use hub motors.	
1900	Because of the brief lead cab bubble, many US automobiles are powered by electricity. By 1915 electric cars dropped to 5% of market share. Electric automobiles were most popular in Chicago, Cleveland and Buffalo.	
1900	The Electric Vehicle Company has a lot of flash equity, mostly as stock shares, to spread around in support of anticipated growth. The Electric Carriage and Wagon, Columbia Motor-Carriage, New Haven Carriage, Riker Electric Vehicle, and Siemens-Halske (North America) companies, are folded into the Electric Vehicle Company, now controlled by a New York/Philadelphia transit holding company known as the "lead cab trust". EVC provides vehicles for the New York City and other taxi companies; the closely tied Electric Storage Battery Company (later ESB Exide) supplied the batteries. In many cases these buyouts are stock swaps where a majority owner of the original company became a minority owner of the briefly inflated conglomerate. The game of the holding company is industry sector monopolies based on patent consolidation and exclusive franchises.	
1900	The electric automobile is in its heyday. Of the 4192 cars produced in the United States 28% are powered by electricity (making this the top-selling vehicle type), and electric vehicles represent 38% of US automobiles (33842 cars in total). The remaining market is split between steam (40%), and gasoline (22%) powered vehicles.	Label 3
1901	Thomas Edison patents the nickel-iron battery.	

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Table A2 – continued from previous page

Year	Event	Major event
1902	Things are already falling apart for the lead cabs. The men running the holding and operating companies are far more successful at selling the companies than their products, and sold more equity stakes than the wildest success might have justified. Although the New York cab company and vehicle manufacturing companies are profitable, and of more value operating than liquidated, the taxi enterprise failed in most other cities. After 1899 the Electrical Vehicle Company does not pay their preferred stock dividend obligations, much less return a dividend on common stock. Several of the original partners, such as Pope, Rice, and Riker, sold out early - were pushed out to a degree - and left the later investors holding a somewhat empty bag. This apparently fraudulent scheme gives quite a blow to the whole concept of electric vehicles in the minds of investors and customers.	Label 4
1902	The Baker Motor Vehicle Co. produces a fully streamlined electric racing car called the Torpedo, with a top speed said to be 120 mph. When it crashed and killed two spectators during its first speed trial at Staten Island Speedway, press toward both speed contests and electric vehicles took a negative turn.	Label 4
1902	Dr. Ferdinand Porsche builds second car, a hybrid with an electric range of 40 miles.	
1903	For Walter C. Baker it is not about top speed, it is about efficiency. In 1903 he builds the Baker Torpedo Kid; it is a one-person vehicle, smaller and far lighter than the 12 HP tandem-seat Torpedo. Most racecar designers increase the power and speed of their cars with each new iteration. Baker has different priorities. The motor in the Kid has a nominal rating of 1½ HP. The Torpedo has no recorded time registered at over 80 mph; The Kid is clocked on Ormond Beach at 103. This record stands for 64 years. It is also the first vehicle to utilise a safety belt. Later, he reportedly reaches 127 mph (204 km/h) but without officially being recorded.	
1905	Rauch & Lang, a well-established maker of luxury coaches in Cleveland, sees the success of nearby Baker and the fading of the horse. They decide to make their coaches electric.	
1905	All makers combined produce approximately 1200 electric motorcars in America.	
1907	Bank panic and recession of 1907: Several of the individuals and their business practices in the lead cab holding Company were involved in causing major bank panic with the collapse of many large banks and a freeze of liquidity, ending many businesses. Although the Electric Vehicle Company had earnings of approx. \$200000 a year from an explosion of car makers paying a royalty on the Seldon patent, and decent earnings from vehicle sales, they were not able to refinance \$2500000 in mortgage backed securities, and went into receivership. At its peak there were 616 cabs and buses in the New York fleet. Gasoline cabs were introduced around 1908 and by 1910 the electric cabs were out of service. This recession was a factor in Henry Ford's decision to make only one model at a low price.	Label 5
1907	Detroit Electric, an electric car produced by the Anderson Electric Car Company, is born. 13000 Detroit Electrics are produced between 1907 and 1939.	

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Table A2 – continued from previous page

Year	Event	Major event
1908	A few months before he sold the first model T, Henry Ford bought Clara her first Detroit Electric (since she preferred electric cars). It had a special child seat for Edsel. The Ford family bought a new Detroit Electric every other year through to 1914.	
1908	Henry Ford introduces the mass-produced and gasoline-powered Model T, which will have a profound effect on the U.S. and global automobile market.	X
1908	Thomas Edison improves the design of his nickel-iron battery.	
1909	William Taft becomes the first U.S. President to purchase an automobile, a Baker Electric.	
1910	Shaft drive electric cars are made the standard by Baker.	
1911	The first gasoline-electric hybrid car is released by Woods Motor Vehicle Company, which is based out of Chicago.	
1912	Charles Kettering invents the first practical electric automobile starter. Ironically, Kettering's invention makes gasoline-powered automobiles more alluring to consumers by eliminating the unwieldy hand crank starter and ultimately helps pave the way for the electric car's demise.	Label 5
1912	Global EV stock reaches historical peak, with 38843 electric vehicles on the roads in the United States	Label 5
1913	Mass production of the Ford Model T on the first modern assembly line deals a strong blow to early-era electric cars, as it brings down the cost of gasoline cars considerably (making electric cars two or even three times more expensive in the coming years). Electric car sales would slowly taper off over the coming years. Main factors leading to the demise of electric cars in the following years and into the 1920s were: cheap Texas oil leading to the ready availability of gasoline; a more developed road network and the ability/desire to travel long distances (electric cars typically had driving ranges of 30 to 40 miles and limited charging infrastructure); the electric starter making petrol-powered vehicles easier and more attractive; the lack of horsepower and slower speeds in electric vehicles (about 20 mph or 32 km/h); tough economic times during World War I; and the stigma that electric cars are for women.	Label 5
1915	The Baker Motor Vehicle Company merges with Rauch & Lang. Only two versions of the Baker Electric are sold through the following year and the Baker brand is only used for industrial trucks through the rest of the Twentieth Century.	
1915	The Milburn Wagon Company is the last important maker of electric pleasure cars to enter the market.	
1916	Venerable Chicago electric vehicle maker Woods introduces a hybrid car called the Woods Dual Power in an attempt to revive the company. This is the most serious attempt at a true hybrid automobile for the general public.	

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Table A2 – continued from previous page

Year	Event	Major event
1919	Only Detroit Electric, Milburn, and Baker, Rauch & Lang survive World War I, the Influenza pandemic, and the postwar recession. Production slowed to a trickle. Electric starting and lighting systems, combined with much more reliable gasoline engines, and better sliding gear transmissions, made the advantages of electric cars less significant.	Label 5
1919	A few serious attempts were made to revive the electric car, notably by Charles Proteus Steinmetz, but none had any market impact.	
1920	During the 1920s the electric car ceases to be a viable commercial product.	X
1923	Milburn, one of few remaining electric vehicle companies, sells out to main body client General Motors.	
1929	W. C. Anderson, 75 years old and in poor health, sells his Detroit Electric company. The last entirely new Detroit Electric was likely sold in 1926.	
1930s	By 1935, EVs become all-but-extinct due to the predominance of internal combustion engine (ICE) vehicles and availability of cheap petrol.	
1947	Oil rationing in Japan leads carmaker Tama to release a 4.5hp electric car with a 40V lead acid battery.	
1957	Sputnik is launched and the US space program engages in advanced battery research & development.	Label 6
1959-61	The Henney Kilowatt, a small electric car, is produced by Henney Coachworks and the National Union Electric Company. It achieves a top speed of 60 mph (97 km/h) and a range of 60 miles (97 kilometres), but its high price keeps away potential buyers.	
1966	Congress introduces the earliest bills recommending use of electric vehicles as a means of reducing air pollution. A Gallup poll indicates that 33 million Americans are interested in electric vehicles.	X
1967	The Electric Auto Association is founded by Walter Laski.	
1967-69	American Motors Corporation (AMC) & Gulton Industries team up to produce a few electric cars using a lithium-based battery and a nickel-cadmium battery, such as the Amitron (1967, lithium batteries) and and all-electric Rambler American (1969, nickel-cadmium batteries). The Amitron introduces regenerative braking.	
1971	The first manned vehicle to drive on the moon, the Lunar Rover, is an electric car.	X
1972	Victor Wouk, the "Godfather of the Hybrid", builds the first full-powered, full-size hybrid vehicle out of a 1972 Buick Skylark provided by General Motors (G.M.) for the 1970 Federal Clean Car Incentive Program. The Environmental Protection Association later kills the program in 1976.	
1972	The Electric Auto Association holds its first annual electric vehicle rally.	
1973	The OPEC oil embargo causes high oil prices, long lines at petrol filling stations, and renewed interested in EVs.	Label 7

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Table A2 – continued from previous page

Year	Event	Major event
1973-77	The Enfield 8000 is built by Enfield Automotive in the UK. Using lead-acid batteries, the car has a top speed of 48 mph (77 km/h) and a top range of about 40 miles (64 kilometres).	
1974	Vanguard-Sebring's CitiCar makes its début at the Electric Vehicle Symposium in Washington, D.C. The CitiCar has a top speed of over 30 mph and a reliable warm-weather range of 40 miles. By 1975 the company is the sixth largest automaker in the U.S. but is dissolved only a few years later.	
1975	The U.S. Postal Service purchases 350 electric delivery Jeeps from AM General, a division of AMC, to be used in a test program.	
1976	Congress passes the Electric and Hybrid Vehicle Research, Development, and Demonstration Act. The law is intended to spur the development of new technologies including improved batteries, motors, and other hybrid-electric components.	Label 7
1976	France's government launches the "PREDIT" programme accelerating EV RD&D.	X
1977	AMC & Gulton Industries again team up to produce the AMC Electron, a 3-passenger, electric, commuter, city car.	
1982	The first modern hybrid car is made at GE Research Lab. It is computer controlled and is the ancestor of current commercial hybrid cars.	Label 8
1983	A fleet of electric vehicles drive from San Jose to San Francisco and back (100 miles / 161 kilometres) without recharging.	
1985	Saied Motai drives an electric vehicle 230 miles (370 kilometres) on a single charge.	
1988	Roger Smith, CEO of G.M., agrees to fund research efforts to build a practical consumer electric car. G.M. teams up with California's AeroVironment to design what would become the EV1, which one employee called "the world's most efficient production vehicle". Some electric vehicle enthusiasts have speculated that the EV1 was never undertaken as a serious commercial venture by the large automaker.	Label 8
1989	Audi creates a hybrid called the "Duo" with NiCad batteries and a 5 cylinder gas engine. The vehicle never sees mainstream production	
1990	General Motors (GM) introduces the GM Impact, an electric concept car, at the Los Angeles Auto Show. GM President Roger Smith also announces that GM will produce electric cars for the consumer market (which finally happens in 1997, but the car is only available to lease).	X

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Table A2 – continued from previous page

Year	Event	Major event
1990	The California Air Resources Board (CARB), the government of California's "clean air agency", pushes for automakers to produce more-fuel-efficient, low-emissions vehicles and eventually transition to zero emissions vehicles (e.g., electric vehicles). The main law is the Zero Emission Vehicle (ZEV) Mandate, which requires 2% of California's vehicles to have 0 tailpipe emissions by 1998, and 10% by 2003. As a result, automakers develop several electric vehicle models in the coming years. However, the automakers do not really get behind the idea, and do not market their electric vehicles well (if at all), and eventually sue CARB, resulting in the repeated weakening and eventual dropping of the ZEV Mandate.	Label 8
1991	The Kewet, a 100% electric microcar produced in Norway, is introduced.	
1992	The Škoda Favorit ELTRA 151L & 151 Pick-Up is released, selling for under $20000 without subsidy. It has a top speed of 50 mph (80 km/h) and a top range of 50 miles (80 kilometres).	
1992	California passes a $1000 tax credit for electric vehicles.	X
1994	12 other US states adopt California's ZEV Mandate.	
1994	The GM Impact EV (later named the EV1) drives 187 mph (301 km/h), breaking the electric vehicle speed record. GM also began PrEView, a program whereby 50 hand-built Impact electric cars would be lent to drivers for periods of 1–2 weeks. This program existed for about 2 years.	X
1994	The REVA Electric Car Company is formed in India, a joint venture between the Maini Group India and AEV of California.	
1995	Toyota debuted a hybrid concept car at the Tokyo Motor Show	
1996	The first 660 EV1s produced are built with GM lead-acid batteries with an advertised range of 70–100 miles (but closer to 60). (Later, they were upgraded to Panasonic lead-acid batteries and had a realistic driving range of 90 miles. Starting in 1999, 457 Gen2 EV1s had NiMh batteries, with a top range of 160 miles.) The EV1 is produced until 2003, but is only available for lease. And GM reclaims and destroys the electric cars, not allowing owners in love with the vehicle to buy them off of GM. EV1s that were donated to engineering schools and museums are not reclaimed but are deactivated, except for the one donated to the Smithsonian. (Honda, Nissan, and Toyota similarly offered their vehicles under closed-ended leases and repossessed/crushed them at the end of the lease periods.)	X
1997	Audi creates the Duo III and it makes it to series production	
1997	Toyota unveils the Prius – the world's first commercially mass-produced and marketed hybrid car – in Japan. Nearly 18000 units are sold during the first production year (1999).	Label 9
1997	GM releases the Chevrolet S10 EV, an electric pickup truck. It has a top speed of 73 mph (118 km/h) and a top range of 90 miles (144 kilometres). It is produced until 1998.	
1997	Honda releases the EV Plus, which has a top speed of over 80 mph (130 km/h) and a top range of 80 to 110 miles (130 to 180 kilometres). It is produced until 1999.	

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Table A2 – continued from previous page

Year	Event	Major event
1997	Toyota releases the RAV4 EV, which has a top speed of 78 mph (125 km/h) and a top range of 87 miles (140 kilometres). It is produced until 2002.	
1998	Nissan produces 200 of the Altra EV from 1998-2002	
1998	Ford releases the Ranger EV, which has a range of 74 miles (119 kilometres). It is produced until 2002.	
1999	The Honda Insight and Toyota Prius, hybrid electric cars, go on sale. These are the first hybrid vehicles on the market since the 1917 Woods hybrid. The Insight comes to the US, while the Prius comes to Japan. (The Prius was introduced in the US 2 years later, in 2001.)	
2001	REVA Electric Car Company releases the REVAi (aka "G-Wiz" in the UK), an electric microcar powered by lead-acid batteries.	
2002	GM and DaimlerChrysler finally sue CARB over the ZEV Mandate, and are joined in the suit by the Bush Administration. They win the lawsuit and the California ZEV Mandate is changed to allow ZEV credits instead of ZEVs.	X
2003	G.M. announces that it will not renew leases on its EV1 cars saying it can no longer supply parts to repair the vehicles and that it plans to reclaim the cars by the end of 2004.	X
2003	Tesla Motors is founded in California.	X
2004	Tesla Motors begins work on the Tesla Roadster, a 100% electric sports car based on the design of the popular and stylish Lotus Elise.	X
2004	The last of the EV1s are taken back from leaseholders and destroyed or donated. All EV1s donated to museums and schools are deactivated, except one. Serial number 660, donated to the Smithsonian, is not disabled.	
2005	On February 16, electric vehicle enthusiasts begin a "Don't Crush" vigil to stop G.M. from demolishing 78 impounded EV1s in Burbank, California. The vigil ends twenty-eight days later when G.M. removes the cars from the facility. In the film "Who Killed the Electric Car?" G.M. spokesman Dave Barthmuss states that the EV1s are to be recycled, not just crushed.	
2005	Who Killed The Electric Car? is released in cinemas.	
2005	Plug In America is launched in the US.	
2006	Tesla Motors publicly unveils the ultra-sporty Tesla Roadster at the San Francisco International Auto Show in November. The first production Roadsters will be sold in 2008 with a base price listing of $98950. The car changes the image of electric cars for many, and also spurs some major automakers to genuinely jump into the electric car market.	Label 10
2007	The Kewet gets rebranded as "Buddy".	
2008	The Th!nk City electric city car goes into production in Norway.	
2008	The Tesla Roadster becomes the first production electric vehicle to use lithium-ion battery cells as well as the first production electric vehicle to have a range of over 200 miles on a single charge.	X

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Year	Event	Major event
2008	January: The Israeli government announces its support for a sweeping project to promote the use of electric cars in Israel. The effort will be a joint venture between Better Place, a Palo Alto start-up founded by software maven Shai Agassi, and French automaker Renault-Nissan. Agassi's plan is to create an extensive network of charging spots and to sell EV drivers mileage in their cars like minutes on a cell phone plan. The first Renault electric cars are scheduled to hit the streets of Tel Aviv and other cities in 2011. Better Place announces a host of partnerships to support electric vehicle projects in Denmark, Canada, Japan, Australia and the U.S.	
2008	July: Oil prices reach more than USD 145 per barrel and car sales drop to their lowest levels in a decade. American automakers begin to shift their production lines away from SUVs and other large vehicles toward smaller, more fuel-efficient cars.	Label 10
2008	August: On the campaign trail, presidential candidate Barack Obama says he will push to have one million plug-in hybrid and electric vehicles on America's roads by 2015.	
2008	November: Struggling to remain profitable during the economic downturn, executives from the Big Three American automakers go to Washington to make the case for a $25 billion Federal bailout of the U.S. automotive industry.	
2008	December: BYD, a Chinese battery manufacturer turned automaker, releases the F3DM, the world's first mass produced plug-in hybrid compact sedan. Though they pack less energy than more conventional lithium ion batteries, BYD opts to power the F3DM with a more stable lithium iron phosphate battery. BYD plans to release the F3DM in the U.S. in 2011, but some industry insiders have doubts about whether the car is ready for the U.S. market. Though sales of the car remain sluggish, Warren Buffett's Berkshire Hathaway purchases a 10% stake in the company.	X
2008	December: The National Bureau of Economic Research states officially that the U.S. has been in a recession since December 2007. The economic downturn is global in scope and will continue to exert financial pressures on the already battered U.S. auto industry.	X
2009	Ford Fusion hybrid is released	
2009	REVA Electric Car Company releases the REVA L-ion, an updated version of its electric microcar this time powered by lithium-ion batteries.	
2009	Tesla unveils the Model S electric sedan, which quickly gets top ratings from leading auto journalists and consumer technology review company Consumer Reports. By many, it is considered the best mass-production car of any type in the world.	X
2009	The Mitsubishi i-MiEV goes on sale in Japan. It hits the European, Chinese, and Australian markets in 2010; and then the US and other markets in 2011.	

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Year	Event	Major event
2009	February: The American Recovery and Reinvestment Act of 2009 allocates $2 billion for development of electric vehicle batteries and related technologies. The Department of Energy adds another $400 million to fund building the infrastructure necessary to support plug-in electric vehicles.	Label 10
2009	April: Prime Minister Gordon Brown announces that the British government will promote the use of electric vehicles in the U.K. by offering a £2000 subsidy to purchasers. A high-ranking government official estimates that 40% of all cars in Britain will need to be electric or hybrid for the country to reach its goal of cutting 80% of its CO2 emissions by 2050.	
2009	April: Chrysler files for Chapter 11 bankruptcy. As part of its restructuring, Chrysler forms a partnership with the Italian car maker Fiat.	
2009	May: President Obama announces a new gas-mileage policy that will require automakers to meet a minimum fuel-efficiency standard of 35.5 miles per gallon by 2016.	
2009	June: General Motors, the leading producer of automobiles for most of the 20th Century, files for bankruptcy protection. While strong GM brands such as Chevrolet, Cadillac and GMC are slated to continue, smaller names like Saturn, Hummer and Pontiac will be sold or closed. The federal government will hold a 61 percent stake in the reborn General Motors.	
2009	June: The Department of Energy awards $8 billion in loans to Ford, Nissan, and Tesla Motors to support the development of fuel-efficient vehicles. The automaker loans are the first distributions from a larger $25 billion fund created under the Energy Independence and Security Act of 2007.	Label 10
2009	August: Nissan unveils its new electric car, called the LEAF ("Leading, Environmentally Friendly, Affordable, Family Car"). The LEAF is capable of a maximum speed of over 90 mph (145 km/h), can travel 100 miles (161 kilometres) on a full charge, and has a battery that can be recharged to 80% of its capacity in 30 minutes. Similar to the Better Place initiative in Israel, Nissan plans to work with the Japanese government and private companies to set up charging station networks across several countries. The first production LEAFs are scheduled to go on sale in Japan, Europe, and the U.S. in the autumn of 2010.	
2010	Mercedes-Benz collaborates with Tesla Motor Company to produce the A-Class E-Cell	
2010	Mass production of the 100% electric Nissan Leaf begins in Japan, and the car is sold in Japan and the US.	Label 11
2010	Production of the BYD e6 begins in China, initially just for fleet customers.	

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Table A2 – continued from previous page

Year	Event	Major event
2010	Mass production of the Chevy Volt, an extended-range electric vehicle (also referred to as a plug-in hybrid electric vehicle), begins in the US. The instigation of this car and possibly all other modern plug-in cars was the Tesla Roadster. Bob Lutz, who was vice chairman of GM at the time, said in 2009: "All the geniuses here at General Motors kept saying lithium-ion technology is 10 years away, and Toyota agreed with us – and boom, along comes Tesla. So I said, 'How come some tiny little California start-up, run by guys who know nothing about the car business, can do this, and we can't?' That was the crowbar that helped break up the log jam".	X
2010	Tesla Motors goes public with an IPO on NASDAQ.	
2010	Approximately 25000 electric cars are on the roads globally (fewer than were on US roads in 1912, but many more than just a few years prior).	X
2011	The world's largest electric car sharing service, Autolib, is launched in Paris with a targeted stock of 3000 EVs.	
2011	French government fleet consortium commits to purchase 50000 EVs over four years.	
2011	Nissan LEAF wins European Car of the Year award.	
2011	The Bolloré Bluecar is released in France, initially just used in Paris' Autolib' carsharing program.	
2011	The Mitsubishi i-MiEV becomes the first electric car to see more than 10000 sales (including under various other badges — Citroën C-Zero and Peugeot iOn).	
2011	Approximately 80000 electric cars are on the roads globally (new historical peak), more than three times the number from the year before.	X
2012	The PHEV Chevrolet Volt outsells half the car models on the U.S. market.	
2012	Tesla unveils the Model X, an electric SUV/crossover with similar performance to the Model S.	X
2012	Tesla begins building a North American Supercharger network, which Tesla owners can use for free.	X
2012	Approximately 200000 electric cars are on the roads globally, 2.5 times more than the year before.	X
2013	The Nissan Leaf becomes the first electric car to see over 50000 sales.	X
2013	The Nissan Leaf gets a $6000 price cut in the US thanks to the start of production in the US (Tennessee).	
2013	For certain months, the Nissan Leaf and the Tesla Model S each become the top-selling car of any type in Norway.	X
2013	The Renault–Nissan Alliance passes 100000 plug-in electric vehicle sales globally, the first company to do so.	
2013	Approximately 405000 electric cars are on the roads globally, more than twice the number from the year before.	X

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Year	Event	Major event
2014	Numerous 100% electric and plug-in hybrid electric vehicles are now on the market, such as: BMW i3, BMW i8, Bolloré Bluecar, BYD e6, BYD Qin, Cadillac ELR, Chevy Spark EV, Chevy Volt, Citröen Berlingo Électrique, Citröen C-Zero, Fiat 500e, Ford C-Max Energi, Ford Fusion Energi, Ford Focus Electric, Honda Accord Plug-in, Honda Fit EV, Kia Soul EV, Mercedes-Benz B-Class Electric, Mia Electric, Mitsubishi i-MiEV, Mitsubishi Outlander Plug-in, Nissan e-NV200, Nissan Leaf, Opel Ampera, Peugeot iOn, Peugeot Partner EV, Porsche Panamera S-E Hybrid, Renault Kangoo ZE, Renault Twizy, Renault Zoe, Smart Electric Drive, Tesla Model S, Tesla Model X, Toyota Prius Plug-in, Toyota RAV4 EV, Via Motors VTRUX SUV/Truck/Van, Volvo C30 Electric, Volvo V60 Plug-in, Volkswagen e-Golf, Volkswagen e-Up!, Volkswagen XL1, Wheego LiFE, Wheego Whip.	
2014	Tesla announces plans to build a battery “gigafactory” in order to ensure it has enough batteries for its current and upcoming vehicles.	X
2014	Tesla opens up its patents to anyone wanting to use them “in good faith”.	X
2014	Tesla announces that its 3rd-generation, much more affordable vehicle will be called Tesla Model 3. It is supposed to have a range of about 200 miles (320 kilometres), be about 20% smaller than the Model S, have a base price of about $30000, and go into production in 2017.	Label 11
2014	Tesla starts working on production of the Model X.	
2014	The Nissan Leaf becomes the first electric car to see over 100000 sales.	Label 11
2017	Tesla begins production and delivery of the Model 3.	

Table A3: Timeline of fibre optics
[Hecht, 2004, Cattani, 2005, 2006, Warf, 2006, Carter, 2009, ETHW.org, 2015b]

Year	Event	Major event
c. 2500 BC	Earliest known glass.	X
Roman Times	Glass is drawn into fibres.	X
1713	Réné de Réaumur makes spun glass fibres.	X
1790s	Claude Chappe invents “optical telegraph” in France.	X
1841	Daniel Colladon demonstrates light guiding in jet of water in Geneva; it also is demonstrated in London and Paris.	X
1842	Daniel Colladon publishes report on light guiding in Comptes Rendus; Jacques Babinet also reports light guiding in water jets and bent glass rods.	X
1853	Paris Opera uses Colladon’s water jet in the opera Faust.	
1854	John Tyndall demonstrates light guiding in water jets at the suggestion of Michael Faraday, duplicating but not acknowledging Colladon.	
1873	Jules de Brunfaut makes glass fibres that can be woven into cloth.	X
1880	Alexander Graham Bell invents Photophone.	X
1880	William Wheeler invents system of light pipes to illuminate homes from an electric arc lamp in basement, Concord, Mass.	X
1884	International Health Exhibition in South Kensington district of London has first fountains with illuminated water jets, designed by Sir Francis Bolton. Colladon republishes his 1842 paper to show the idea was his.	
1887	Charles Vernon Boys draws quartz fibres for mechanical measurements.	X
1887	Royal Jubilee Exhibition in Manchester has illuminated “Fairy Fountains” designed by W. and J. Galloway and Sons.	
1888	Dr. Roth and Prof. Reuss of Vienna use bent glass rods to illuminate body cavities for dentistry and surgery.	X
1889	Universal Exhibition in Paris shows refined illuminated fountains designed by G. Bechmann.	
1892	Herman Hammesfahr shows glass dress at Chicago World’s Fair.	
1895	Henry C. Saint-René designs a system of bent glass rods for guiding light in an early television scheme (Crezancy, France).	X
1898	David D. Smith of Indianapolis applies for patent on bent glass rod as a surgical lamp.	X
1920s	Bent glass rods common for microscope illumination.	X
1926	2nd June: C. Francis Jenkins applies for US patent on a mechanical television receiver in which light passes along quartz rods in a rotating drum to form an image.	X

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Table A3 – continued from previous page

Year	Event	Major event
1926	15th October: John Logie Baird applies for British patent on an array of parallel glass rods or hollow tubes to carry image in a mechanical television. He later built an array of hollow tubes.	X
1926	30th December: Clarence W. Hansell proposes a fibre-optic imaging bundle in his notebook at the RCA Rocky Point Laboratory on Long Island. He later receives American and British patents.	X
1930	Heinrich Lamm, a medical student, assembles first bundle of transparent fibres to carry an image (of an electric lamp filament) in Munich. His effort to file a patent is denied because of Hansell's British patent.	X
1931	December: Owens-Illinois mass-produces glass fibres for Fibreglass.	X
1932	20th August: Norman French of Bell Labs applies for patent on an "optical telephone system" using quartz rods.	X
Mid-1930s	Frank Hyde develops flame hydrolysis to make fused silica at Corning Glass Works.	X
1939	Curvlite Sales offers illuminated tongue depressor and dental illuminators made of Lucite, a transparent plastic invented by DuPont.	
1945	31st October: Ray D. Kell and George Sziklai apply for patent on transmitting signals through quartz or glass rods, issued May 9, 1950.	Label 1
c. 1949	Holger Møller Hansen in Denmark and Abraham C. S. van Heel at the Technical University of Delft begin investigating image transmission through bundles of parallel glass fibres.	X
1951	11th April: Holger Møller Hansen applies for a Danish patent on fibre-optic imaging in which he proposes cladding glass or plastic fibres with a transparent low-index material. Patent claim is denied because of Hansell patent.	X
1951	October: Brian O'Brien (University of Rochester) suggests to van Heel that applying a transparent cladding would improve transmission of fibres in his imaging bundle.	
1952	July: Harold Horace Hopkins applies for a grant from the Royal Society to develop bundles of glass fibres for use as an endoscope at Imperial College of Science and Technology. Hires Narinder S. Kapany as an assistant after he receives grant.	X
Early 1953	O'Brien joins American Optical as vice president and research director. His top priority is developing a wide-screen movie system for promoter Mike Todd; fibre optics is sidetracked.	
Spring 1953	Hopkins tells Fritz Zernicke his idea of fibre bundles; Zernicke tells van Heel, who decides to publish quickly.	
1953	21st May: Nature receives brief paper by van Heel on simple bundles of clad fibres.	
1953	12th June: Dutch-language weekly De Ingeneur publishes van Heel's first report of clad fibre.	
1953	22nd November: Nature receives paper on bundles of unclad fibres for imaging written by Hopkins and Kapany.	

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Table A3 – continued from previous page

Year	Event	Major event
1954	2nd January: Nature publishes papers by Hopkins and Kapany and by van Heel. The long delay of the van Heel paper has never been explained.	Label 2
1954	Basil Hirschowitz visits Hopkins and Kapany in London from the University of Michigan.	
1954	September: American Optical hires Will Hicks to develop fibre-optic image scramblers, proposed by O'Brien to the Central Intelligence Agency.	
Summer 1955	Kapany completes doctoral thesis on fibre optics under Hopkins, moves to University of Rochester.	
Summer 1955	Hirschowitz and C. Wilbur Peters hire undergraduate student Larry Curtiss to work on their fibre-optic endoscope project.	
1956	First transatlantic telephone cable, TAT-1, goes into operation. It uses coaxial cable to carry 36 voice circuits.	X
Summer 1956	Curtiss suggests making glass-clad fibres by melting a tube onto a rod of higher-index glass. Peters and other Michigan physicists push plastic-clad fibres, which Curtiss makes instead.	
1956	October: Frederick H. Norton starts consulting with American Optical on fibre development. Later he suggests ways to make glass cladding.	
1956	October: Curtiss and Peters describe plastic-clad fibres at Optical Society of America meeting in Lake Placid, New York. Kapany also presents a paper. Hicks attends but does not give a talk.	X
1956	8th December: Curtiss makes first glass-clad fibres by rod-in-tube method; they are much clearer than plastic-clad fibres.	
1957	18th February: Hirschowitz tests first fibre-optic endoscope in a patient.	Label 3
Early 1957	Hicks experiments with glass-clad fibres and fusing many fibres into a rigid bundle, an idea suggested by Norton.	
1957	May: Hirschowitz demonstrates fibre endoscope to American Gastroscopic Society.	Label 3
Mid-1957	Kapany leaves Rochester to head group at Illinois Institute of Technology Research Institute in Chicago.	
Mid-1957	Image scrambler project ends after Hicks tells CIA the code is easy to break. American Optical shifts to developing faceplates, adding more people as Todd-AO wide-screen movie project fades.	
1957	Hirschowitz, Peters, and Curtiss licence gastroscope technology to American Cystoscope Manufacturers Inc.	
Late 1957–Early 1958	Charles Townes and Arthur Schawlow outline principles of laser operation. Gordon Gould starts work on his own laser proposal.	Label 3
Early 1958	Hicks develops practical fibre-optic faceplates for military imaging systems.	

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Table A3 – continued from previous page

Year	Event	Major event
1958	Hicks, Paul Kiritsy, and Chet Thompson leave American Optical to form Mosaic Fabrications in Southbridge, Mass., the first fibre optics company.	
1958	Alec Reeves begins investigating optical communications at Standard Telecommunication Laboratories.	
1959	Working with Hicks, American Optical draws fibres so fine they transmit only a single mode of light. Elias Snitzer recognises the fibres as single-mode waveguides and applies for a patent (with Hicks) in 1960.	Label 3
1960	16th May: Theodore Maiman demonstrates the first laser at Hughes Research Laboratories in Malibu.	Label 3
1960	12th December: Ali Javan makes first helium-neon laser at Bell Labs, the first laser to emit a steady beam.	X
c. 1960	George Goubau at Army Electronics Command Laboratory, Stew Miller of Bell Telephone Laboratories, and Murray Ramsay of Standard Telecommunication Laboratories begin investigating confocal optical waveguides with regularly spaced lenses.	
1961	January: Charles C. Eaglesfield of STL proposes hollow optical pipeline made of reflective pipes.	
1961	May: Eli Snitzer of American Optical publishes theoretical description of single-mode fibres.	X
1961	Narinder Kapany founds Optics Technology Inc.	
1962	Experiments at STL show high loss in Eaglesfield's hollow optical pipeline.	
1962	AT&T starts converting to digital telephone transmission.	
1962	September-October: Four groups nearly simultaneously make first semiconductor diode lasers, which emit pulses at liquid-nitrogen temperature. Robert N. Hall's group at General Electric is first.	X
1962	Dwight Berreman of Bell Labs proposes gas lens waveguide.	
1962-63	STL abandons millimetre waveguide development. Alec Reeves pushes optical waveguides but sees problems with confocal lens waveguides.	
1962-63	Experiments show high loss when sending laser beams through atmosphere.	
1963	Heterostructures proposed for semiconductor lasers.	
1963-64	Antoni E. Karbowiak of STL realises that unclad transparent optical waveguides would have to be impractically thin. He considers clad optical fibres, but thinks a flexible thin-film waveguide would have lower loss.	
1964	October: Charles Koester and Eli Snitzer describe first optical amplifier, using neodymium-doped glass.	X

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Table A3 – continued from previous page

Year	Event	Major event
1964	December: Charles K. Kao takes over STL optical communication program when Karbowiak leaves to become chair of electrical engineering at the University of New South Wales. Kao and George Hockham soon abandon thin-film waveguide in favour of single-mode clad optical fibre.	
1965	February: Stewart Miller of Bell Labs applies for patent on graded-index waveguides for light and millimetre waves.	
Autumn 1965	Kao concludes that the fundamental limit on glass transparency is below 20 decibels per kilometre, which would be practical for communications. Hockham calculates that clad fibres should not radiate much light. They prepare a paper proposing fibre-optic communications.	Label 4
1966	January: Kao tells Institution of Electrical Engineers in London that glass fibres could be made with loss below 20 decibels per kilometre for communications.	Label 4
Early 1966	F. F. Roberts starts fibre-optic communications research at British Post Office Research Laboratories.	
1966	July: Kao and Hockham publish paper outlining their proposal in Proceedings of the Institution of Electrical Engineers.	X
1966	July: John Galt at Bell Labs asks Mort Panish and Izuo Hayashi to figure out why diode lasers have high thresholds at room temperature.	
1966	September: Alain Werts, a young engineer at CSF in France, publishes proposal similar to Kao's in French-language journal L'Onde Electronique, but CSF does nothing further for lack of funding.	
1966	Roberts tells William Shaver, a visitor from the Corning Glass Works, about interest in fibre communications. This leads Robert Maurer to start a small research project on fused-silica fibres.	
1966	Kao travels to America early in the year but fails to interest Bell Labs. He later finds more interest in Japan.	
Early 1967	British Post Office allocates an extra £12 million to research; some goes to fibre optics.	X
Early 1967	Shojiro Kawakami of Tohoku University in Japan proposes graded-index optical fibres.	
Summer 1967	Corning summer intern Cliff Fonstad makes fibres with Frank Zimar. Loss is high, but Maurer decides to continue the research using titania-doped cores and pure-silica cladding.	
1967	October: Clarence Hansell dies at 68.	
Late 1967	Robert Maurer recruits Peter Schultz from Corning's glass chemistry department to help make pure glasses.	
1968	January: Donald Keck starts work for Maurer as the first full-time fibre developer at Corning.	

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Table A3 – continued from previous page

Year	Event	Major event
1968	August: Dick Dyott of British Post Office picks up suggestion for pulling clad optical fibres from molten glass in a double crucible.	
1968	Kao and M. W. Jones measure intrinsic loss of bulk fused silica at 4 decibels per kilometre, the first evidence of ultratransparent glass, prompting Bell Labs to seriously consider fibre optics.	Label 4
1969	Martin Chown of Standard Telecommunication Labs (STL) demonstrates fibre-optic repeater at Physical Society exhibition.	Label 4
1970	April: STL demonstrates fibre-optic transmission at Physics Exhibition in London.	Label 4
Spring 1970	First continuous-wave room-temperature semiconductor lasers made in early May by Zhores Alferov's group at the Ioffe Physical Institute in Leningrad (now St. Petersburg) and on June 1 by Mort Panish and Izuo Hayashi at Bell Labs.	Label 4
1970	30th June: AT&T introduces Picturephone in Pittsburgh. The telephone monopoly plans to install millimetre waveguides to provide the needed extra capacity.	
Summer 1970	Maurer, Donald Keck, and Peter Schultz at Corning make a single-mode fibre with loss of 16 decibels per kilometre at 633 nanometres by doping titanium into fibre core.	Label 4
1970	30th September: Maurer announces Corning's fibre results at London conference devoted mainly to progress in millimetre waveguides.	
1970	November: Measurements at British Post Office and STL confirm Corning results.	X
Late Autumn 1970	Charles Kao leaves STL to teach at Chinese University of Hong Kong; Murray Ramsay heads STL fibre group.	
1970-71	Dick Dyott at British Post Office and Felix Kapron of Corning separately find pulse spreading is lowest at 1.2 to 1.3 micrometres.	X
1971	May: Murray Ramsay of STL demonstrates digital video transmission over fibre to Queen Elizabeth at the Centenary of the Institution of Electrical Engineers.	X
1971	13th October: Alec Reeves dies in London.	
1971-72	Unable to duplicate Corning's low loss, Bell Labs, the University of Southampton, and CSIRO in Australia experiment with liquid-core fibres.	
1971-72	Focus shifts to graded-index fibres because single-mode offers few advantages and many problems at 850 nanometres.	
1972	June: Maurer, Keck, and Schultz make multimode germania-doped fibre with 4 decibel per kilometre loss and much greater strength than titania-doped fibre.	X
Late 1972	STL modulates diode laser at 1 billion bits per second. Bell Labs stops work on hollow light pipes.	
1972	December: John Fulenwider proposes a fibre-optic communication network to carry video signals to homes at International Wire and Cable Symposium.	Label 5

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Table A3 – continued from previous page

Year	Event	Major event
1973	John MacChesney develops modified chemical vapour deposition process for making fibre at Bell Labs.	
Mid-1973	Diode laser lifetime reaches 1000 hours at Bell Labs.	X
Spring 1974	Bell Labs settles on graded-index fibres with 50 to 100 micrometre cores.	
1974	7th December: Heinrich Lamm dies at 66.	
1975	January: First technical meeting, Topical Conference on Optical Fibre Transmission, Williamsburg, Virginia.	
1975	February: Bell completes installation of 14 kilometres of millimetre waveguide in New Jersey. After tests, Bell declares victory and abandons the technology.	Label 6
1975	June: First commercial continuous-wave semiconductor laser operating at room temperature offered by Laser Diode Labs.	X
1975	September: First non-experimental fibre-optic link installed by Dorset (UK) police after lightning knocks out their communication system.	Label 6
1975	October: British Post Office begins tests of millimetre waveguide; like Bell it declares the tests successful, but never installs any.	
1975	Dave Payne and Alex Gambling at University of Southampton calculate pulse spreading should be zero at 1.27 micrometres.	Label 6
1976	13th January: Bell Labs starts tests of graded-index fibre-optic system transmitting 45 million bits per second at its plant in Norcross, Georgia. Laser lifetime is main problem.	
Early 1976	Valtec launches Communications Fiberoptics division.	
Early 1976	Masaharu Horiguchi (Nippon Telegraph Telephone Ibaraki Lab) and Hiroshi Osanai (Fujikura Cable) make first fibres with low loss—0.47 decibel per kilometre—at long wavelengths (1.2 micrometres).	Label 6
1976	March: Japan's Ministry for International Trade and Industry announces plans for Hi-OVIS fibre-optic "wired city" experiment involving 150 homes.	Label 6
Spring 1976	Lifetime of best laboratory lasers at Bell Labs reaches 100000 hours (10 years) at room temperature.	Label 6
Summer 1976	Horiguchi and Osanai discover third fibre-optic transmission window at 1.55 micrometres.	X
1976	July: Corning sues ITT alleging infringement of American patents on communication fibres.	
Late 1976	J. Jim Hsieh makes indium-gallium arsenidephosphide (InGaAsP) lasers emitting continuously at 1.25 micrometres.	
Spring 1977	F. F. Roberts reaches mandatory retirement age of 60; John Midwinter becomes head of fibre-optic group at British Post Office.	
1977	1st April: AT&T sends first test signals through field test system in Chicago's Loop district.	Label 6

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Year	Event	Major event
1977	22nd April: General Telephone and Electronics sends first live telephone traffic through fibre optics (6 million bits per second) in Long Beach, Calif.	Label 6
1977	May: Bell System starts sending live telephone traffic through fibres at 45 million bits per second fibre link in downtown Chicago.	Label 6
1977	June: British Post Office begins sending live telephone traffic through fibres in underground ducts near Martlesham Heath.	
1977	29th June: Bell Labs announces one million hour (100 year) extrapolated lifetime for diode lasers.	Label 6
Summer 1977	F. F. Roberts dies of heart attack.	
1977	October: Valtec "acquires" Comm/Scope, but Comm/Scope owners soon gain control of Valtec.	
Late 1977	AT&T and other telephone companies settle on 850-nanometre gallium arsenide light sources and graded-index fibres for commercial systems operating at 45 million bits per second.	X
1977-78	Low loss at long wavelengths renews research interest in single-mode fibre.	X
1978	22nd - 23rd May: Fiber Optic Con, first fibre-optic trade show.	
1978	July: Optical fibres begin carrying signals to homes in Japan's Hi-OVIS project.	X
1978	August: Nippon Telegraph and Telephone transmits 32 million bits per second through a record 53 kilometres of graded-index fibre at 1.3 micrometres.	
1978	September: Richard Epworth reports modal noise problems in graded-index fibres.	X
1978	September: France Telecom announces plans for fibre to the home demonstration in Biarritz, connecting 1500 homes in early 1983.	
1978	AT&T, British Post Office, and Standard Telephones and Cables commit to developing a single-mode transatlantic fibre cable, using the new 1.3-micrometre window, to be operational by 1988. By the end of the year, Bell Labs abandons development of new coaxial cables for submarine systems.	Label 6
Late 1978	NTT Ibaraki lab makes single-mode fibre with record 0.2 decibel per kilometre loss at 1.55 micrometres.	X
1980	January: AT&T asks Federal Communications Commission to approve Northeast Corridor system from Boston to Washington, designed to carry three different wavelengths through graded-index fibre at 45 million bits per second.	
1980	February: STL and British Post Office lay 9.5-kilometre submarine cable in Loch Fyne, Scotland, including single-mode and graded-index fibres.	X
1980	September: With fibre optics hot on the stock market, M/A Com buys Valtec for $224 million in stock.	

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Year	Event	Major event
Winter 1980	Graded-index fibre system carries video signals for 1980 Winter Olympics in Lake Placid, New York, at 850 nanometres.	
1980	Bell Labs publicly commits to single-mode 1.3-micrometre technology for the first transatlantic fibre-optic cable, TAT-8.	X
1981	27th July: ITT signs consent agreement to pay Corning and licence Corning communication fibre patents.	
1981	Commercial second-generation systems emerge, operating at 1.3 micrometres through graded-index fibres.	X
1981	British Telecom transmits 140 million bits per second through 49 kilometres of single-mode fibre at 1.3 micrometres, starts shifting to single-mode.	
Late 1981	Canada begins trial of fibre optics to homes in Elie, Manitoba.	
1982	British Telecom performs field trial of single-mode fibre, abandons graded-index in favour of singlemode.	X
1982	December: MCI leases right of way to install single-mode fibre from New York to Washington. The system will operate at 400 million bits per second at 1.3 micrometres. This starts the shift to single-mode fibre in America.	
Late 1983	Stew Miller retires as head of Bell Labs fibre development group.	
1984	1st January: AT&T undergoes first divestiture, splitting off its seven regional operating companies but keeping long-distance transmission and equipment manufacture.	
1984	British Telecom lays first submarine fibre cable to carry regular traffic, to the Isle of Wight.	Label 7
1985	Single-mode fibre spreads across America to carry long-distance telephone signals at 400 million bits per second and up.	
Summer 1986	All 1500 Biarritz homes connected to fibre to the home system.	
1986	30th October: First fibre-optic cable across the English Channel begins service.	Label 7
1986	AT&T sends 1.7 billion bits per second through single-mode fibres.	X
Early 1987	David Payne reports making the first erbium-doped optical fibre amplifier at the University of Southampton.	X
1987	November: Emmanuel Desurvire develops model to predict behaviour of erbium optical amplifier at Bell Labs.	
1988	January: Eli Snitzer reports that erbium amplifiers can be pumped at 1.48 micrometres.	
1988	Linn Mollenauer of Bell Labs demonstrates soliton transmission through 4000 kilometres of single-mode fibre.	
1988	December: TAT-8, first transatlantic fibre-optic cable, begins service using 1.3-micrometre lasers and single-mode fibre.	Label 7

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Year	Event	Major event
Early 1989	Emmanuel Desurvire measures very low crosstalk when signals are transmitted through an erbium amplifier at two separate wavelengths, pointing toward wavelength division multiplexing.	
1989	November: NTT reports gain of 46.5 decibels in erbium amplifier excited by 1.48 micrometre laser.	
1990	January: KDD transmits 2.4 billion bit per second signals at 4 wavelengths through 6 erbium amplifiers and 459 kilometres of fibre.	
1991	February: Neal Bergano of Bell Labs transmits five billion bits per second through 9000 kilometres of fibre. That design later selected for TAT-12 cable.	X
1991	February: Masataka Nakazawa of NTT sends soliton signals through a million kilometres of fibre.	
1991	February: Mollenauer transmits solitons at two wavelengths through 9000 kilometres of fibre.	
1993	February: Mollenauer transmits 10 billion bits per second through 20000 kilometres of fibres with a simple soliton system.	
1994	World Wide Web grows from 500 to 10000 servers.	X
1995	February: NTT transmits 10 billion bits per second on each of 16 wavelengths through 1000 kilometres of fibre using dispersion compensation.	
1995-96	Internet traffic hits peak growth, doubling in 3–4 months.	
1996	February: Fujitsu, NTT Labs, and Bell Labs all report sending one trillion bits per second through single fibres in separate experiments.	X
1996	Commercial wavelength-division multiplexing systems introduced.	
1996	TAT-12 transatlantic cable put in service, the first with optical amplifiers.	X
1996	October: Lucent Technologies splits from AT&T, taking most of Bell Labs.	
1997	15th May: Amazon.com has initial public offering of stock early in Internet boom.	
1998	February: NTT transmits 1 trillion bits per second through a series of optical amplifiers and 600 kilometres of fibre; Bell Labs does similar experiment through 400 kilometres of fibre.	
1998	First long-distance submarine cables with wavelength-division multiplexing. Commercial systems transmit dozens of wavelengths at 2.5 billion bits per second. Developers promise systems transmitting 10 billion bits per second on dozens of channels.	X
1999	February: NTT reaches three trillion bits per second through 40 kilometres of fibre.	
1999	NASDAQ average nearly doubles as the bubble takes off.	
2000	7th - 10th March: NASDAQ hits record high of 5132.52. Optical Fiber Communication Conference attracts record crowd of 16934 to Baltimore.	
2000	July: Peak of telecom bubble. JDS Uniphase announces plans to merge with SDL Inc. in stock deal valued at $41 billion.	Label 8

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Year	Event	Major event
2001	19th - 22nd March: Optical Fiber Communication Conference attracts record crowd of 38015 to Anaheim, with 970 companies exhibiting.	
2001	22nd March: NEC Corp. reports transmitting 10.92 trillion bits per second through 117 kilometres of fibre.	
Spring & Summer 2001	Telecom bubble deflates and stocks tumble. Layoffs begin.	Label 9
2001	December: TAT-8 submarine cable fails. It is later retired because repairs would be too expensive and other transatlantic cables have extra capacity.	X
2002	21st July: WorldCom files for bankruptcy, the largest bankruptcy in U.S. corporate history.	Label 9
2003	January: Total transatlantic transmission capacity in use is 2700 billion bits per second, about 5000 times that of TAT-8. Total potential capacity is 12300 billion bits per second.	

Table A4: Timeline of geothermal electricity
[Tester et al., 2012, U.S. Department of Energy, 2018, EIA, 2008d,b]

Year	Event	Major event
1807	As European settlers moved westward across the continent, they gravitated toward warm springs. In 1807, the first European to visit the Yellowstone area, John Colter, probably encountered hot springs, leading to the designation "Colter's Hell". Also in 1807, settlers founded the city of Hot Springs, Arkansas, where, in 1830, Asa Thompson charged one dollar each for the use of three spring-fed baths in a wooden tub, making this the first known commercial use of geothermal energy.	X
1847	William Bell Elliot, a member of John C. Fremont's survey party, stumbles upon a steaming valley just north of what is now San Francisco, California. Elliot calls the area The Geysers—a misnomer—and thinks he has found the gates of Hell.	
1852	The Geysers is developed into a spa called The Geysers Resort Hotel. Guests include J. Pierpont Morgan, Ulysses S. Grant, Theodore Roosevelt, and Mark Twain.	
1862	At springs located south-east of The Geysers, businessman Sam Brannan pours an estimated half million dollars into an extravagant development dubbed "Calistoga", replete with hotel, bathhouses, skating pavilion, and racetrack. Brannan's was one of many spas reminiscent of those of Europe.	
1864	Homes and dwellings have been built near springs through the millennia to take advantage of the natural heat of these geothermal springs, but the construction of the Hot Lake Hotel near La Grande, Oregon, marks the first time that the energy from hot springs is used on a large scale.	X
1892	Residents in Boise, Idaho, receive the world's first district heating system as water is piped from hot springs to town buildings. Within a few years, the system is serving 200 homes and 40 downtown businesses. By 2013, there were four district heating systems in Boise that provide heat to over 5 million square feet of residential, business, and governmental space. Although no one imitated this system for some 70 years, as of 2013 there are 17 district heating systems in the United States and dozens more around the world.	Label 1
1900	Hot springs water is piped to homes in Klamath Falls, Oregon.	Label 2
1904	The first dry steam geothermal power plant was built in Larderello in Tuscany, Italy, by Prince Piero Ginori Conti. The Larderello plant today provides power to about 1 million households.	Label 3
1921	John D. Grant drills a well at The Geysers with the intention of generating electricity. This effort is unsuccessful, but one year later Grant meets with success across the valley at another site, and the United States' first geothermal power plant goes into operation. Grant uses steam from the first well to build a second well, and, several wells later, the operation is producing 250 kilowatts, enough electricity to light the buildings and streets at the resort. The plant, however, is not competitive with other sources of power, and it soon falls into disuse.	

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Year	Event	Major event
1921	Hot Springs National Park in Arkansas is created.	
1927	Pioneer Development Company drills the first exploratory wells at Imperial Valley, California.	
1930	The first commercial greenhouse use of geothermal energy is undertaken in Boise, Idaho. The operation uses a 1000-foot well drilled in 1926. In Klamath Falls, Charlie Lieb develops the first downhole heat exchanger (DHE) to heat his house. As of 2013, more than 500 DHEs are in use around the US.	Label 4
1940	The first residential space heating in Nevada begins in the Moana area in Reno.	
1948	Geothermal technology moves east when Professor Carl Nielsen of Ohio State University develops the first ground-source heat pump, for use at his residence. J.D. Krocker, an engineer in Portland, Oregon, pioneers the first commercial building use of a groundwater heat pump.	Label 5
1958	New Zealand builds the first new Geothermal electricity powerplant since Larderello	Label 6
1960	The United States' first large-scale geothermal electricity-generating plant begins operation. Pacific Gas and Electric operates the plant, located at The Geysers. The first turbine produces 11 megawatts (MW) of net power and operates successfully for more than 30 years. By 2013, 69 generating facilities are in operation at 18 resource sites around the US.	Label 6
1970	Re-injection of spent geothermal water back into the production reservoir was introduced as a way to dispose of waste water and to extend reservoir life.	
1970	The Geothermal Resources Council is formed to encourage development of geothermal resources worldwide.	Label 7
1970	The Geothermal Steam Act is enacted, which provides the US Secretary of the Interior with the authority to lease public lands and other federal lands for geothermal exploration and development in an environmentally sound manner.	X
1972	Deep well drilling technology improvements led to deeper reservoir drilling and to access to more resources.	
1972	The Geothermal Energy Association is formed. The association includes U.S. companies that develop geothermal resources worldwide for electrical power generation and direct-heat uses.	X
1973	The Arab Oil Embargo occurred, in which several Arab nations in the Organization of Petroleum Exporting Countries (OPEC) embargoed oil to the United States and Holland to protest their support of Israel in the Arab-Israeli "Yom Kippur" War. Arab OPEC production was cut by 25%, which caused some temporary shortages and helped oil prices to triple. This contributed to an increased interest in alternatives to petroleum, including geothermal power.	Label 8
1973	The National Science Foundation becomes the lead agency for federal geothermal programs.	

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Year	Event	Major event
1974	Scientists began to develop the first hot dry rock (HDR) reservoir at Fenton Hill, New Mexico. An HDR power facility was tested at the site in 1978 and started to generate electricity two years later.	
1974	The U.S. government enacts the Geothermal Energy Research, Development and Demonstration (RD&D) Act, instituting the Geothermal Loan Guaranty Program, which provides investment security to public and private sectors using developing technologies to exploit geothermal resources.	X
1975	The Energy Research and Development Administration (ERDA) is formed in the U.S. The Division of Geothermal Energy takes over the RD&D program. The Geo-Heat Center is formed. The center, located at the Oregon Institute of Technology, disseminates information to potential users and conducts applied research on using low- to moderate-temperature geothermal resources. The U.S. Geological Survey releases the first national geothermal resource estimate and inventory.	X
1977	The U.S. Department of Energy (DOE) is formed.	X
1978	U.S. Department of Energy (DOE) funding for geothermal research and development was increased substantially.	X
1978	The Public Utility Regulatory Policies Act (PURPA) is enacted in the U.S. PURPA encourages the development of independent, non-utility cogeneration and small power projects by requiring electric utilities to interconnect with them. The act results in the development of several water-dominated resources.	
1978	Geothermal Food Processors, Inc., opens the first geothermal food-processing (crop-drying) plant in Brady Hot Springs, Nevada. The Loan Guaranty Program provides $3.5 million for the facility.	
1978	A hot dry rock geothermal facility is created and tested in Fenton Hill, New Mexico, with financial assistance from DOE. The facility generates electricity two years later, in 1980.	X
1979	The first electrical development of a water-dominated geothermal resource occurs, at the East Mesa field in the Imperial Valley in California. The plant is named for B.C. McCabe, the geothermal pioneer who, with his Magma Power Company, did field development work at several sites, including The Geysers.	
1979	DOE institutes funding of direct-use demonstration projects. Among the beneficiaries of this effort are several office buildings, district heating systems, and agribusinesses.	
1980s	California's Standard Offer Contract system for PURPA-qualifying facilities provided renewable electric energy systems a relatively firm, stable market for output, allowing the financing of capital-intensive technologies like geothermal energy facilities.	X
1980	The first commercial-scale binary plant in the United States began operation in Southern California's Imperial Valley.	Label 9

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Year	Event	Major event
1980	TAD's Enterprises of Nevada pioneers the use of geothermal energy for the cooking, distilling, and drying processes associated with alcohol fuels production. UNOCAL builds the country's first flash plant, generating 10 MW at Brawley, California.	
1981	With a supporting loan from DOE, Ormat successfully demonstrates binary technology in the Imperial Valley of California. This project establishes the technical feasibility of larger-scale commercial binary power plants. The project is so successful that Ormat repays the loan within a year.	X
1981	The first electricity is generated from geothermal resources in Hawaii. The Department of Energy demonstrates the production of electricity from moderate temperature geothermal resources using binary technology at Raft River, Idaho.	
1982	Geothermal (hydrothermal) electric generating capacity, reached a new high of 1000 megawatts.	X
1982	Economical electrical generation begins at California's Salton Sea geothermal field through the use of crystalliser-clarifier technology. The technology resulted from a government/industry effort to manage the high-salinity brines at the site.	
1984	A 20-MW plant begins commercially generating power at Utah's Roosevelt Hot Springs. Nevada's first geothermal electricity is generated when a 1.3-MW binary power plant begins operation.	
1984	The Heber dual-flash power plant goes online in the Imperial Valley of California with 50 MW.	
1986-2000	Decline, on the average, of fossil energy prices in constant dollars saps motivation for vigorous pursuit of the more expensive categories of alternatives. This is then reinvigorated by post-2000 oil price escalation	Label 10
1987	Geothermal fluids are used in the first geothermal-enhanced heap leaching project for gold recovery, near Round Mountain, Nevada.	
1989	The world's first hybrid (organic Rankine/gas engine) geopressure-geothermal power plant (1 MW) begins operation at Pleasant Bayou, Texas, using both the heat and the methane of a geopressured resource.	Label 10
1990	DOE funding for geothermal energy research and development declined throughout the 1980s and reached a low of $15 million.	Label 10
1991	The world's first magma exploratory well was drilled in the Sierra Nevada Mountains to a depth of 7588 feet.	
1991	The Bonneville Power Administration selects three sites in the Pacific Northwest for geothermal demonstration projects.	
1992	Electrical generation begins at the 25-MW geothermal plant in the Puna field of Hawaii.	
1993	A 23-MW binary power plant is completed at Steamboat Springs, Nevada.	

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Year	Event	Major event
1994	California Energy became the world's largest geothermal company through its acquisition of Magma Power.	
1994	DOE creates two industry/government collaborative efforts to promote the use of geothermal energy to reduce greenhouse gas emissions. One effort is directed toward the accelerated development of geothermal resources for electric power generation; the other is aimed toward the accelerated use of geothermal heat pumps.	Label 11
1995	Worldwide geothermal capacity reached 6000 megawatts.	X
1995	Integrated Ingredients dedicates a food-dehydration facility that processes 15 million pounds of dried onions and garlic per year at Empire, Nevada. A DOE low-temperature resource assessment of 10 western states identifies nearly 9000 thermal wells and springs and 271 communities collocated with a geothermal resource greater than 50ºC.	
1999	California's geothermal power plants provided 54.9% of the State's electricity.	X
2000	DOE initiates its GeoPowering the West program to encourage development of geothermal resources in the western U. S. An initial group of 21 partnerships with industry is funded to develop new technologies.	
2001	GeoPowering the West brings together representatives from industry and agencies such as the U.S. Bureau of Land Management and U.S. Forest Service to identify major barriers to geothermal development in the west. The report of the proceedings listed specific action items and recommendations. Several of the recommendations pertained to leasing, permitting, and access to federal lands.	
2001	US Secretary of the Interior Gail Norton convened a renewable energy summit with officials from DOI, DOE, and other agencies to identify actions required to support renewable energy development. Recommendations specific to geothermal emerged from the meeting, including a mandate to BLM to accelerate issuing leases and permits on federal lands.	
2002	Organised by GeoPowering the West, geothermal development working groups are active in five states — Nevada, Idaho, New Mexico, Oregon, and Washington. Group members represent all stakeholder organizations. The working groups are identifying barriers to geothermal development in their state, and bringing together all interested parties to arrive at mutually beneficial solutions.	
2003	The Utah Geothermal Working Group is formed.	
2004	Geothermal energy costs dropped from \$.10 - .16 per kilowatt hour to \$.5 - .8 per kilowatt hour.	X

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Year	Event	Major event
2005	The Energy Policy Act of 2005 was signed into law. It changed U.S. energy policy by providing tax incentives and loan guarantees for various types of energy production. It included provisions aimed at making geothermal energy more competitive with fossil fuels in generating electricity. The Act amended the Geothermal Steam Act of 1970 to modify how royalties are calculated, how land is leased, and how federal income from geothermal development is distributed.	Label 12
2005	According to the U.S. Department of Interior's Bureau of Land Management, geothermal energy generated over 14800 GWh of electricity in 2005, enough power to supply the annual needs of 1.3 million homes.	
2006	The U.S. geothermal industry became a $1.5 billion a year business that involved electricity generation and thermal energy in direct use such as indoor heating, greenhouses, food drying, aquaculture.	
2006	Alaska installed a 200 kilowatt power plant that used low-temperature (74ºC) geothermal water along with cooling water (4ºC).	
2007	The Energy Independence and Security Act of 2007 which includes the Advanced Geothermal Research and Development Act of 2007 provided authorization and direction for DOE's geothermal research activities.	
2008	Idaho's first commercial geothermal power plant began operating.	
2009	Through the American Recovery and Reinvestment Act (ARRA) of 2009, the Geothermal Technologies Office awarded $368.2 million to 149 geothermal projects in 38 states and the District of Columbia.	Label 13
2010	In FY 2010, the DOE Geothermal Technologies Office contributed $786000 to the Small Business Innovation Research (SBIR) Program and $94000 to the Small Business Technology Transfer (STTR) program for geothermal projects.	
2011/2012	According to the Geothermal Energy Association (GEA) Annual U.S. Geothermal Power Production and Development Report, the U.S. geothermal industry continued to grow steadily in 2011 and through the first quarter of 2012. Geothermal companies increased installed capacity from 3102 MW to 3187 MW over this time frame.	
2012	The Enhanced Geothermal Systems (EGS) field demonstration project achieves a steam production equivalent of five megawatts at an abandoned part of The Geysers field in Northern California, encouraging expectations that this vast energy source (100+ GW) can be further developed and scaled up for nationwide deployment in the long-term.	
2013	In 2013, the Desert Peak project completes an 8-month, multi-stage stimulation of an existing but underperforming well, successfully validating fluid injection and stimulation increases to levels within the magnitude of a commercial well, and dramatically increasing flow rate. This project is the first EGS project in America to generate commercial electricity by providing an additional 1.7 MW at the existing well-field.	

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Year	Event	Major event
2013	In April, a DOE investment deploys a project that takes advantage of close-looped geothermal power generation—as a thermal by-product of gold mining—to generate essentially emission-free electricity for less than 6 cents/kWh. This patented plug-and-play technology is the first in the US to employ cost-free geothermal brine at a mine operation and the technology is thought to have the potential for broader applications in many parts of the US and globally, including oil and gas operations, establishing a commercially deployable clean energy enterprise.	

Table A5: Timeline of hydro electricity [Smil, 2004, EIA, 2009]

Year	Event	Major event
B.C.	Hydropower was used by the Greeks to turn water wheels for grinding grains more than 2000 years ago.	
1753	French hydraulic and military engineer Bernard Forest de Belidor wrote Architecture Hydraulique, a four-volume work describing vertical- and horizontal-axis machines.	
1832	Reaction water turbine developed by Benoit Fourneyron	Label 1
1847	Inward-flow water turbine developed by James B. Francis	Label 2
1880-95	Hydropower was beginning to be used for electricity. The first hydroelectric plants were direct current (DC) stations used to power nearby arc and incandescent lighting.	
1880	Michigan's Grand Rapids Electric Light and Power Company generated DC electricity, using hydropower at the Wolverine Chair Factory. A dynamo belted to a water turbine at the factory generated electricity to light 16 brush-arc lamps in the store front.	Label 3
1881	Street lamps in the city of Niagara Falls were powered by hydropower (direct current).	Label 3
1882	The world's first central DC hydroelectric station provided power for a paper mill in Appleton, Wisconsin.	Label 3
1886	Between 40 to 50 hydroelectric plants were operating in the United States and in Canada.	
1888	About 200 electric companies relied on hydropower for at least part of their generation.	
1889	Pelton machines (jet-driven turbines) introduced	Label 4
1889	The first AC hydroelectric plant in the US, Williamette Falls Station, began operation in Oregon City, Oregon.	X
1893	The Austin Dam, near Austin, Texas, was completed. It was the first dam specifically designed for generating hydropower.	Label 5
1895-96	The Niagara Falls hydropower station opened. It originally provided electricity to the local area. One year later, when a new AC power line was opened, electric power from Niagara Falls was sent to customers over 20 miles away in Buffalo, New York.	Label 5
1901	The first Federal Water Power Act required special permission for a hydroelectric plant to be built and operated on any stream large enough for boat traffic.	Label 6
1902	The Reclamation Act of 1902 created the United States Reclamation Service, later renamed the U.S. Bureau of Reclamation. The Reclamation Service was formed to manage water resources and was given the authority to build hydropower plants at dams.	
1905	The Reclamation Service installed a hydropower plant at the Arizona construction site of the Theodore Roosevelt Dam. The power plant was originally built to provide electricity for constructing the dam, but sales of extra electricity helped pay for the project and improved life in the local community.	
1920	Federal Power Act established the Federal Power Commission (later replaced by the Federal Energy Regulatory Commission) to issue licences for hydropower development on public lands in the U.S.	Label 7

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Table A5 – continued from previous page

Year	Event	Major event
1933	The Tennessee Valley Authority (TVA) was established to take charge of the hydroelectric potential of the Mississippi River in the Tennessee Valley.	
1933	Construction of the Grand Coulee Dam began on the Columbia River. Originally built to meet irrigation needs, it had more electric generating capacity than any other dam in North America.	
1935	Federal Power Commission authority was extended to all hydroelectric projects built by utilities engaged in interstate commerce.	
1936	Boulder Dam (later renamed the Hoover Dam) began operating on the Colorado River. The hydropower plant produced up to 130000 kilowatts of electricity.	Label 8
1937	The U.S. Army Corp of Engineers finished the Bonneville Dam, on the Columbia River in Oregon and Washington.	
1937	The Bonneville Power Administration (BPA) was established.	
1941	Grand Coulee, the United States' largest hydroelectric dam, began operation.	Label 9
1949	Almost one-third of the United States' electricity came from hydropower.	
1961	The Columbia River Treaty was signed between the United States and Canada. Under the treaty, Canada built two dams for storage and one dam for generation. This resulted in greater power and flood control, which benefited U.S. facilities downstream.	
1977	The Federal Power Commission was disbanded by Congress. A new agency was created, the Federal Energy Regulatory Commission (FERC), to regulate energy production and transmission.	
1978	Congress passed the Public Utility Regulatory Policies Act (PURPA) of 1978. The Act required utilities to purchase electricity from qualified independent power producers. Portions of the Act stimulated growth of small-scale hydro plants to help meet the United States' energy needs.	Label 10
1980	Conventional hydropower plant capacity nearly tripled in United States since 1940.	Label 10
1980	Poor salmon runs in the Columbia River system prompted Congress to pass the Pacific Northwest Power Planning and Conservation Act of 1980. This Act established the Northwest Power Planning Council, responsible for the protection and recovery of salmon runs in the Columbia River system. These laws resulted in a more complex, expensive process to obtain a licence for a hydroelectric facility.	Label 10
1986	Congress amended the Federal Power Act to increase the environmental review of hydropower projects.	
1988	The Northwest Power Planning Council designated 44000 miles of Pacific Northwest streams as protected areas because of their importance as critical fish and wildlife habitats.	
1994	Court ruled that the 1993 Biological Opinion, which guided coordinated use of the Columbia River System, failed to meet legal standards associated with the Endangered Species Act.	

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Year	Event	Major event
2006	The United States ranked among the Top 4 countries in the world for hydroelectric generation, along with China, Canada, and Brazil. These countries generated 44% of the world's electricity from hydropower.	Label 11
2009	Between 6% and 10% of U.S. electricity comes from hydropower, depending on water supply and annual rainfall. In total, the United States has about 80000 megawatts of conventional capacity and 18000 megawatts of pumped storage capacity.	

Table A6: Timeline of the internet [Zakon, 1997]

Year	Event	Major event
1957	USSR launches Sputnik, first artificial earth satellite. In response, US forms the Advanced Research Projects Agency (ARPA), the following year, within the Department of Defense (DoD) to establish US lead in science and technology applicable to the military	Label 1
1961	Leonard Kleinrock, MIT: "Information Flow in Large Communication Nets" (May 31): First paper on packet-switching (PS) theory	Label 2
1962	J.C.R. Licklider & W. Clark, MIT: "On-Line Man Computer Communication" (August): Galactic Network concept encompassing distributed social interactions	Label 2
1964	Paul Baran, RAND: "On Distributed Communications Networks": Packet-switching networks; no single outage point	Label 2
1965	ARPA sponsors study on "cooperative network of time-sharing computers": TX-2 at MIT Lincoln Lab and AN/FSQ-32 at System Development Corporation (Santa Monica, CA) are directly linked (without packet switches) via a dedicated 1200bps phone line; Digital Equipment Corporation (DEC) computer at ARPA later added to form "The Experimental Network"	Label 3
1966	Lawrence G. Roberts, MIT: "Towards a Cooperative Network of Time-Shared Computers" (October): First ARPANET plan	Label 3
1967	ARPANET design discussions held by Larry Roberts at ARPA IPTO PI meeting in Ann Arbor, Michigan (April)	X
1967	National Physical Laboratory (NPL) in Middlesex, England develops NPL Data Network under Donald Watts Davies who coins the term packet. The NPL network, an experiment in packet-switching, used 768kbps lines	X
1967	ACM Symposium on Operating Systems Principles in Gatlinburg, Tennessee (October): First design paper on ARPANET published by Larry Roberts: "Multiple Computer Networks and Intercomputer Communication", first meeting of the three independent packet network teams (RAND, NPL, ARPA)	Label 3
1968	PS-network presented to the Advanced Research Projects Agency (ARPA)	
1968	Request for quotation for ARPANET (29 Jul) sent out in August; responses received in September	
1968	University of California Los Angeles (UCLA) awarded Network Measurement Center contract in October	
1968	Network Working Group (NWG), headed by Steve Crocker, loosely organised to develop host level protocols for communication over the ARPANET.	
1968	Tymnet built as part of Tymshare service	
1969	Bolt Beranek and Newman, Inc. (BBN) awarded Packet Switch contract to build Interface Message Processors (IMPs) in January	

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Table A6 – continued from previous page

Year	Event	Major event
1969	US Senator Edward Kennedy sends a congratulatory telegram to BBN for its million-dollar ARPA contract to build the "Interfaith" Message Processor, and thanking them for their ecumenical efforts	
1969	ARPANET commissioned by DoD for research into networking	Label 4
1969	First Request for Comment (RFC): "Host Software" by Steve Crocker (7 April)	
1969	First packets sent by Charley Kline at UCLA as he tried logging into SRI. The first attempt resulted in the system crashing as the letter G of LOGIN was entered. (October 29)	Label 4
1969	Univ of Michigan, Michigan State and Wayne State Univ establish X.25-based Merit network for students, faculty, alumni	
1970	First publication of the original ARPANET Host-Host protocol: C.S. Carr, S. Crocker, V.G. Cerf, "HOST-HOST Communication Protocol in the ARPA Network", in AFIPS Proceedings of SJCC	Label 4
1970	First report on ARPANET at AFIPS: "Computer Network Development to Achieve Resource Sharing" (March)	X
1970	ALOHAnet, the first packet radio network, developed by Norman Abramson, Univ of Hawaii, becomes operational (July): connected to the ARPANET in 1972	Label 4
1970	ARPANET hosts start using Network Control Protocol (NCP), first host-to-host protocol	Label 4
1970	First cross-country link installed by AT&T between UCLA and BBN at 56kbps. This line is later replaced by another between BBN and RAND. A second line is added between MIT and Utah	
1971	15 nodes (23 hosts): UCLA, SRI, UCSB, Univ of Utah, BBN, MIT, RAND, SDC, Harvard, Lincoln Lab, Stanford, UIU(C), CWRU, CMU, NASA/Ames	
1971	BBN starts building IMPs using the cheaper Honeywell 316. IMPs however are limited to 4 host connections, and so BBN develops a terminal IMP (TIP) that supports up to 64 terminals (September)	
1971	Ray Tomlinson of BBN invents email program to send messages across a distributed network. The original program was derived from two others: an intra-machine email program (SENDMSG) and an experimental file transfer program (CPYNET)	Label 4
1971	Project Gutenberg is started by Michael Hart with the purpose of making copyright-free works, including books, electronically available. The first text is the US Declaration of Independence	
1972	Ray Tomlinson (BBN) modifies email program for ARPANET where it becomes a quick hit. The @ sign was chosen from the punctuation keys on Tomlinson's Model 33 Teletype for its "at" meaning (March)	X
1972	Larry Roberts writes first email management program (RD) to list, selectively read, file, forward, and respond to messages (July)	X

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Table A6 – continued from previous page

Year	Event	Major event
1972	International Conference on Computer Communications (ICCC) at the Washington D.C. Hilton with demonstration of ARPANET between 40 machines and the Terminal Interface Processor (TIP) organised by Bob Kahn. (October)	X
1972	First computer-to-computer chat takes place at UCLA, and is repeated during ICCC, as psychotic PARRY (at Stanford) discusses its problems with the Doctor (at BBN).	X
1972	International Network Working Group (INWG) formed in October as a result of a meeting at ICCC identifying the need for a combined effort in advancing networking technologies. Vint Cerf appointed first Chair. By 1974, INWG became IFIP WG 6.1	
1972	Louis Pouzin leads the French effort to build its own ARPANET - CYCLADES	X
1973	First international connections to the ARPANET: University College of London (England) via NORSAR (Norway)	Label 5
1973	Bob Metcalfe's Harvard PhD Thesis outlines idea for Ethernet. The concept was tested on Xerox PARC's Alto computers, and the first Ethernet network called the Alto Aloha System (May)	X
1973	Bob Kahn poses Internet problem, starts Internetting research program at ARPA. Vinton Cerf sketches gateway architecture in March on back of envelope in a San Francisco hotel lobby	X
1973	Cerf and Kahn present basic Internet ideas at INWG in September at Univ of Sussex, Brighton, UK	X
1973	Network Voice Protocol (NVP) specification (RFC 741) and implementation enabling conference calls over ARPAnet.	
1973	SRI (NIC) begins publishing ARPANET News in March; number of ARPANET users estimated at 2000	
1973	ARPA study shows email composing 75% of all ARPANET traffic	
1973	Christmas Day Lockup - Harvard IMP hardware problem leads it to broadcast zero-length hops to any ARPANET destination, causing all other IMPs to send their traffic to Harvard (25 December)	
1974	Vint Cerf and Bob Kahn publish "A Protocol for Packet Network Intercommunication" which specified in detail the design of a Transmission Control Program (TCP). [IEEE Trans Comm]	Label 5
1974	BBN opens Telenet, the first public packet data service (a commercial version of ARPANET)	X
1975	Operational management of Internet transferred to DCA (now DISA)	
1975	First ARPANET mailing list, MsgGroup, is created by Steve Walker. Einar Stefferud soon took over as moderator as the list was not automated at first. A science fiction list, SF-Lovers, was to become the most popular unofficial list in the early days	

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Year	Event	Major event
1975	John Vittal develops MSG, the first all-inclusive email program providing replying, forwarding, and filing capabilities.	X
1975	Satellite links cross two oceans (to Hawaii and UK) as the first TCP tests are run over them by Stanford, BBN, and UCL	X
1976	Queen Elizabeth II sends out an email on 26 March from the Royal Signals and Radar Establishment (RSRE) in Malvern (UK)	
1976	UUCP (Unix-to-Unix CoPy) developed at AT&T Bell Labs and distributed with UNIX one year later.	
1976	Multiprocessing Pluribus IMPs are deployed	
1977	THEORYNET created by Larry Landweber at Univ of Wisconsin providing electronic mail to over 100 researchers in computer science (using a locally developed email system over TELENET)	
1977	Tymshare spins out Tymnet under pressure from TELENET. Both go on to develop X.25 protocol standard for virtual circuit style packet switching	
1977	First demonstration of ARPANET/SF Bay Packet Radio Net/Atlantic SATNET operation of Internet protocols with BBN-supplied gateways in July	
1978	TCP split into TCP and IP (March)	Label 6
1978	Possibly the first commercial spam message is sent on 1 May by a DEC marketer advertising an upcoming presentation of its new DECSYSTEM-20 computers	X
1979	Meeting between Univ of Wisconsin, DARPA, National Science Foundation (NSF), and computer scientists from many universities to establish a Computer Science Department research computer network (organised by Larry Landweber).	X
1979	USENET established using UUCP between Duke and UNC by Tom Truscott, Jim Ellis, and Steve Bellovin. All original groups were under NET.* hierarchy.	
1979	ARPA establishes the Internet Configuration Control Board (ICCB)	X
1979	Packet Radio Network (PRNET) experiment starts with DARPA funding. Most communications take place between mobile vans. ARPANET connection via SRI.	X
1979	On April 12, Kevin MacKenzie emails the MsgGroup a suggestion of adding some emotion back into the dry text medium of email, such as -) for indicating a sentence was tongue-in-cheek. Though flamed by many at the time, emoticons became widely used after Scott Fahlman suggested the use of :-) and :-(in a CMU BBS on 19 September 1982	
1980	ARPANET grinds to a complete halt on 27 October because of an accidentally-propagated status-message virus	X

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Table A6 – continued from previous page

Year	Event	Major event
1981	BITNET, the "Because It's Time NETwork": Started as a cooperative network at the City University of New York, with the first connection to Yale; original acronym stood for 'There' instead of 'Time' in reference to the free NJE protocols provided with the IBM systems; provides electronic mail and listserv servers to distribute information, as well as file transfers	X
1981	CSNET (Computer Science NETwork) built by a collaboration of computer scientists and Univ of Delaware, Purdue Univ, Univ of Wisconsin, RAND Corporation and BBN through seed money granted by NSF to provide networking services (especially email) to university scientists with no access to ARPANET. CSNET later becomes known as the Computer and Science Network.	X
1981	Minitel (Teletel) is deployed across France by France Telecom.	
1982	Norway leaves network to become an Internet connection via TCP/IP over SATNET; UCL does the same	
1982	DCA and ARPA establish the Transmission Control Protocol (TCP) and Internet Protocol (IP), as the protocol suite, commonly known as TCP/IP, for ARPANET: this leads to one of the first definitions of an "internet" as a connected set of networks, specifically those using TCP/IP, and "Internet" as connected TCP/IP internets. DoD declares TCP/IP suite to be standard for DoD.	Label 7
1982	EUnet (European UNIX Network) is created by EUUG to provide email and USENET services (original connections between the Netherlands, Denmark, Sweden, and UK)	X
1982	Exterior Gateway Protocol (RFC 827) specification. EGP is used for gateways between networks.	X
1983	Name server developed at Univ of Wisconsin, no longer requiring users to know the exact path to other systems	X
1983	Cutover from NCP to TCP/IP (1 January)	Label 7
1983	Stuttgart and Korea get connected	
1983	Movement Information Net (MINET) started early in the year in Europe, connected to Internet in Sept	
1983	CSNET / ARPANET gateway put in place	X
1983	ARPANET split into ARPANET and MILNET; the latter became integrated with the Defense Data Network created the previous year. 68 of the 113 existing nodes went to MILNET	Label 7
1983	Desktop workstations come into being, many with Berkeley UNIX (4.2 BSD) which includes IP networking software	
1983	Networking needs switch from having a single, large time sharing computer connected to the Internet at each site, to instead connecting entire local networks	
1983	Internet Activities Board (IAB) established, replacing ICCB	X

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Year	Event	Major event
1983	EARN (European Academic and Research Network) established. Very similar to the way BITNET works with a gateway funded by IBM-Europe	X
1984	Domain Name System (DNS) introduced	X
1984	Number of hosts breaks 1000	X
1984	JUNET (Japan Unix Network) established using UUCP	
1984	JANET (Joint Academic Network) established in the UK using the Coloured Book protocols; previously SERCnet	X
1984	Moderated newsgroups introduced on USENET (mod.*)	
1984	Canada begins a one-year effort to network its universities. The NetNorth Network is connected to BITNET in Ithaca from Toronto	
1984	Kremvax message announcing USSR connectivity to USENET	X
1985	Whole Earth 'Lectronic Link (WELL) started	
1985	Information Sciences Institute (ISI) at USC is given responsibility for DNS root management by DCA, and SRI for DNS NIC registrations	
1985	Symbolics.com is assigned on 15 March to become the first registered domain. Other firsts: cmu.edu, purdue.edu, rice.edu, berkeley.edu, ucla.edu, rutgers.edu, bbn.com (24 Apr); mit.edu (23 May); think.com (24 may); css.gov (June); mitre.org, .uk (July)	
1985	100 years to the day of the last spike being driven on the cross-Canada railroad, the last Canadian university is connected to NetNorth in a one year effort to have coast-to-coast connectivity.	
1986	NSFNET created (backbone speed of 56Kbps). NSF establishes 5 super-computing centers to provide high-computing power for all (JVNC@Princeton, PSC@Pittsburgh, SDSC@UCSD, NCSA@UIUC, Theory Center@Cornell). This allows an explosion of connections, especially from universities.	Label 8
1986	Internet Engineering Task Force (IETF) and Internet Research Task Force (IRTF) comes into existence under the IAB. First IETF meeting held in January at Linkabit in San Diego	
1986	The first Freenet (Cleveland) comes on-line 16 July under the auspices of the Society for Public Access Computing (SoPAC). Later Freenet program management assumed by the National Public Telecomputing Network (NPTN) in 1989	
1986	Network News Transfer Protocol (NNTP) designed to enhance Usenet news performance over TCP/IP.	X
1986	Mail Exchanger (MX) records developed by Craig Partridge allow non-IP network hosts to have domain addresses.	
1986	The first in a series of congestion collapses begin occurring in October.	X
1986	The great USENET name change; moderated newsgroups changed in 1987.	
1986	BARRNET (Bay Area Regional Research Network) established using high speed links. Operational in 1987.	

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Table A6 – continued from previous page

Year	Event	Major event
1986	New England gets cut off from the Net as AT&T suffers a fibre optics cable break between Newark/NJ and White Plains/NY. All seven New England ARPANET trunk lines were in the one severed cable. Outage took place between 1:11 and 12:11 EST on 12 December	X
1987	NSF signs a cooperative agreement to manage the NSFNET backbone with Merit Network, Inc. (IBM and MCI involvement was through an agreement with Merit). Merit, IBM, and MCI later founded ANS.	
1987	UUNET is founded with Usenix funds to provide commercial UUCP and Usenet access. Originally an experiment by Rick Adams and Mike O'Dell	
1987	First TCP/IP Interoperability Conference (March), name changed in 1988 to INTEROP	
1987	Email link established between Germany and China using CSNET protocols, with the first message from China sent on 20 September.	
1987	The concept and plan for a national US research and education network is proposed by Gordon Bell et al in a report to the Office of Science and Technology, written in response to a congressional request by Al Gore. (Nov) It would take four years until the establishment of this network by Congress	X
1987	Number of hosts breaks 10000	
1987	Number of BITNET hosts breaks 1000	
1988	2 November - Internet worm burrows through the Net, affecting approximately 6000 of the 60000 hosts on the Internet	
1988	CERT (Computer Emergency Response Team) formed by DARPA in response to the needs exhibited during the Morris worm incident. The worm is the only advisory issued this year.	X
1988	DoD chooses to adopt OSI and sees use of TCP/IP as an interim. US Government OSI Profile (GOSIP) defines the set of protocols to be supported by Government purchased products	
1988	Los Nettos network created with no federal funding, instead supported by regional members (founding: Caltech, TIS, UCLA, USC, ISI).	
1988	NSFNET backbone upgraded to T1 (1.54Mbps)	
1988	CERFnet (California Education and Research Federation network) founded by Susan Estrada.	
1988	Internet Assigned Numbers Authority (IANA) established in December with Jon Postel as its Director. Postel was also the RFC Editor and US Domain registrar for many years.	
1988	Internet Relay Chat (IRC) developed by Jarkko Oikarinen	
1988	First Canadian regionals join NSFNET: ONet via Cornell, RISQ via Princeton, BCnet via Univ of Washington	
1988	The first multicast tunnel is established between Stanford and BBN in the Summer of 1988.	
1988	Countries connecting to NSFNET: Canada (CA), Denmark (DK), France (FR), Iceland (IS), Norway (NO), Sweden (SE)	

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Table A6 – continued from previous page

Year	Event	Major event
1989	Number of hosts breaks 100000	X
1989	RIPE (Reseaux IP Europeens) formed (by European service providers) to ensure the necessary administrative and technical coordination to allow the operation of the pan-European IP Network.	
1989	First relays between a commercial electronic mail carrier and the Internet: MCI Mail through the Corporation for the National Research Initiative (CNRI), and CompuServe through Ohio State Univ	
1989	Corporation for Research and Education Networking (CREN) is formed by merging CSNET into BITNET (August)	
1989	AARNET - Australian Academic Research Network - set up by AVCC and CSIRO; introduced into service the following year	X
1989	First link between Australia and NSFNET via Hawaii on 23 June. Australia had been limited to USENET access since the early 1980s	
1989	UCLA sponsors the Act One symposium to celebrate ARPANET's 20th anniversary and its decommissioning (August)	
1989	Countries connecting to NSFNET: Australia (AU), Germany (DE), Israel (IL), Italy (IT), Japan (JP), Mexico (MX), Netherlands (NL), New Zealand (NZ), Puerto Rico (PR), United Kingdom (UK)	
1990	ARPANET ceases to exist	Label 9
1990	Electronic Frontier Foundation (EFF) is founded by Mitch Kapor	
1990	The World comes on-line (world.std.com), becoming the first commercial provider of Internet dial-up access	X
1990	ISO Development Environment (ISODE) developed to provide an approach for OSI migration for the DoD. ISODE software allows OSI application to operate over TCP/IP	
1990	CA*net formed by 10 regional networks as national Canadian backbone with direct connection to NSFNET	
1990	The first remotely operated machine to be hooked up to the Internet, the Internet Toaster by John Romkey, (controlled via SNMP) makes its début at Interop.	X
1990	Countries connecting to NSFNET: Argentina (AR), Austria (AT), Belgium (BE), Brazil (BR), Chile (CL), Greece (GR), India (IN), Ireland (IE), Korea (KR), Spain (ES), Switzerland (CH)	
1991	First connection takes place between Brazil, by Fapesp, and the Internet at 9600 baud.	
1991	Commercial Internet eXchange (CIX) Association, Inc. formed by General Atomics (CERFnet), Performance Systems International, Inc. (PSInet), and UUNET Technologies, Inc. (AlterNet), as NSF lifts restrictions on the commercial use of the Net (March)	
1991	Wide Area Information Servers (WAIS), invented by Brewster Kahle, released by Thinking Machines Corporation	

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Year	Event	Major event
1991	Gopher released by Paul Lindner and Mark P. McCahill from the Univ of Minnesota	
1991	World-Wide Web (WWW) released by CERN; Tim Berners-Lee developer. First Web server is nxoc01.cern.ch, launched in Nov 1990 and later renamed info.cern.ch.	Label 9
1991	US High Performance Computing Act (Gore 1) establishes the National Research and Education Network (NREN)	X
1991	NSFNET backbone upgraded to T3 (44.74Mbps)	
1991	NSFNET traffic passes 1 trillion bytes/month and 10 billion packets/month	
1991	Defense Data Network NIC contract awarded by DISA to Government Systems Inc. who takes over from SRI on 1 Oct	
1991	Start of JANET IP Service (JIPS) which signalled the changeover from Coloured Book software to TCP/IP within the UK academic network. IP was initially 'tunnelled' within X.25.	
1992	Internet Society (ISOC) is chartered under CNRI (January); incorporation took place in December	
1992	IAB reconstituted as the Internet Architecture Board and becomes part of the Internet Society	
1992	Number of hosts breaks 1000000	X
1992	First MBONE audio multicast (March) and video multicast (November)	
1992	RIPE Network Coordination Center (NCC) created in April to provide address registration and coordination services to the European Internet community	
1992	Veronica, a gopherspace search tool, is released by Univ of Nevada	
1992	World Bank comes on-line	
1992	The term "surfing the Internet" is coined by Jean Armour Polly; Brendan Kehoe uses the term "net-surfing" as early as 6 June 1991 in a USENET post	
1993	InterNIC created by NSF to provide specific Internet services: directory and database services (AT&T); registration services (Network Solutions Inc.); information services (General Atomics/CERFnet)	
1993	US White House email comes on-line at whitehouse.gov; web site launches in 1994	
1993	Worms of a new kind find their way around the Net - WWW Worms (W4), joined by Spiders, Wanderers, Crawlers, and Snakes ...	
1993	Internet Talk Radio begins broadcasting	
1993	United Nations (UN) comes on-line	
1993	US National Information Infrastructure Act	
1993	Businesses and media begin taking notice of the Internet	X
1993	InterCon International KK (IIKK) provides Japan's first commercial Internet connection in September. TWICS, though an IIKK leased line, begins offering dial-up accounts the following month	

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Table A6 – continued from previous page

Year	Event	Major event
1993	Mosaic takes the Internet by storm (22 Apr); WWW proliferates at a 341634% annual growth rate of service traffic. Gopher's growth is 997%.	Label 10
1994	ARPANET/Internet celebrates 25th anniversary	
1994	Communities begin to be wired up directly to the Internet (Lexington and Cambridge, Mass., USA)	
1994	US Senate and House provide information servers	
1994	Shopping malls arrive on the Internet	Label 10
1994	First cyberstation, RT-FM, broadcasts from Interop in Las Vegas	
1994	Arizona law firm of Canter & Siegel "spams" the Internet with email advertising green card lottery services; Net citizens flame back	
1994	NSFNET traffic passes 10 trillion bytes/month	
1994	WWW edges out telnet to become 2nd most popular service on the Net (behind ftp-data) based on % of packets and bytes traffic distribution on NSFNET	
1994	First Virtual, the first cyberbank, open up for business	X
1994	Radio stations start rockin' (rebroadcasting) round the clock on the Net: WXYC at Univ of NC, KJHK at Univ of KS-Lawrence, KUGS at Western WA Univ	X
1994	The first banner ads appear on hotwired.com in October. They were for Zima (a beverage) and AT&T	X
1994	Trans-European Research and Education Network Association (TERENA) is formed by the merger of RARE and EARN, with representatives from 38 countries as well as CERN and ECMWF. TERENA's aim is to "promote and participate in the development of a high quality international information and telecommunications infrastructure for the benefit of research and education" (October)	
1994	The first web-based machine translation system is developed by this Timeline's author, supporting 9 languages, and made available the following year to hundreds of thousands of users on OSIS and Intelink, both US government networks	
1994	Countries connecting to NSFNET: Algeria (DZ), Armenia (AM), Bermuda (BM), Burkina Faso (BF), China (CN), Colombia (CO), Jamaica (JM), Jordan (JO), Lebanon (LB), Lithuania (LT), Macao (MO), Morocco (MA), New Caledonia (NC), Nicaragua (NI), Niger (NE), Panama (PA), Philippines (PH), Senegal (SN), Sri Lanka (LK), Swaziland (SZ), Uruguay (UY), Uzbekistan (UZ)	
1995	NSFNET reverts back to a research network. Main US backbone traffic now routed through interconnected network providers	X
1995	The new NSFNET is born as NSF establishes the very high speed Backbone Network Service (vBNS) linking super-computing centers: NCAR, NCSA, SDSC, CTC, PSC	
1995	Hong Kong police disconnect all but one of the colony's Internet providers for failure to obtain a licence; thousands of users are left without service	

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Year	Event	Major event
1995	Sun launches JAVA on May 23	X
1995	RealAudio, an audio streaming technology, lets the Net hear in near real-time	
1995	Radio HK, the first commercial 24 hr., Internet-only radio station starts broadcasting	
1995	WWW surpasses ftp-data in March as the service with greatest traffic on NSFNET based on packet count, and in April based on byte count	
1995	Traditional online dial-up systems (CompuServe, America Online, Prodigy) begin to provide Internet access	
1995	Chris Lamprecht (aka "Minor Threat") becomes the first person banned from accessing the Internet by a US District Court judge in Texas	
1995	Thousands in Minneapolis-St. Paul (USA) lose Net access after transients start a bonfire under a bridge at the Univ of MN causing fibre-optic cables to melt (30 July)	
1995	A number of Net related companies go public, with Netscape leading the pack with the 3rd largest ever NASDAQ IPO share value (9 August)	
1995	Registration of domain names is no longer free. Beginning 14 September, a $50 annual fee has been imposed, which up until now was subsidised by NSF. NSF continues to pay for .edu registration, and on an interim basis for .gov	
1995	The first official Internet wiretap was successful in helping the Secret Service and Drug Enforcement Agency (DEA) apprehend three individuals who were illegally manufacturing and selling cell phone cloning equipment and electronic devices	
1995	Operation Home Front connects, for the first time, soldiers in the field with their families back home via the Internet.	
1995	Technologies of the Year: WWW, Search engines	
1995	Emerging Technologies: Mobile code (JAVA, JAVAscript), Virtual environments (VRML), Collaborative tools	
1996	Internet phones catch the attention of US telecommunication companies who ask the US Congress to ban the technology (which has been around for years)	
1996	The controversial US Communications Decency Act (CDA) becomes law in the US in order to prohibit distribution of indecent materials over the Net. A few months later a three-judge panel imposes an injunction against its enforcement. Supreme Court unanimously rules most of it unconstitutional in 1997.	
1996	BackRub, Google's precursor, comes online	Label 10
1996	Various ISPs suffer extended service outages, bringing into question whether they will be able to handle the growing number of users. AOL (19 hours), Netcom (13 hours), AT&T WorldNet (28 hours - email only)	
1996	New York's Public Access Networks Corp (PANIX) is shut down after repeated SYN attacks by a cracker using methods outlined in a hacker magazine (2600)	

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Table A6 – continued from previous page

Year	Event	Major event
1996	MCI upgrades Internet backbone adding approximately 13000 ports, bringing the effective speed from 155Mbps to 622Mbps.	
1996	A malicious cancelbot is released on USENET wiping out more than 25000 messages	
1996	The WWW browser war, fought primarily between Netscape and Microsoft, has rushed in a new age in software development, whereby new releases are made quarterly with the help of Internet users eager to test upcoming (beta) versions.	X
1996	Internet2 project is kicked off by representatives from 34 universities on 1 Oct	
1996	Restrictions on Internet use around the world: China: requires users and ISPs to register with the police; Germany: cuts off access to some newsgroups carried on CompuServe; Saudi Arabia: confines Internet access to universities and hospitals; Singapore: requires political and religious content providers to register with the state; New Zealand: classifies computer disks as "publications" that can be censored and seized (source: Human Rights Watch)	
1996	Technologies of the Year: Search engines, JAVA, Internet Phone	
1996	Emerging Technologies: Virtual environments (VRML), Collaborative tools, Internet appliance (Network Computer)	
1997	71618 mailing lists registered at Liszt, a mailing list directory	
1997	The American Registry for Internet Numbers (ARIN) is established to handle administration and registration of IP numbers to the geographical areas currently handled by Network Solutions (InterNIC), starting March 1998.	
1997	CA*net II launched in June to provide Canada's next generation Internet using ATM/SONET	
1997	Domain name business.com sold for US$150000	
1997	Early in the morning of 17 July, human error at Network Solutions causes the DNS table for .com and .net domains to become corrupted, making millions of systems unreachable.	
1997	101803 Name Servers in whois database	
1997	Technologies of the Year: Push, Multicasting	
1997	Emerging Technologies: Push	
1998	US Depart of Commerce (DoC) releases the Green Paper outlining its plan to privatise DNS on 30 January. This is followed up by a White Paper on June 5	
1998	Web size estimates range between 275 (Digital) and 320 (NEC) million pages for 1Q	X
1998	Internet users get to be judges in a performance by 12 world champion ice skaters on 27 March, marking the first time a television sport show's outcome is determined by its viewers.	
1998	Network Solutions registers its 2 millionth domain on 4 May	
1998	Electronic postal stamps become a reality, with the US Postal Service allowing stamps to be purchased and downloaded for printing from the Web.	
1998	Canada kicks off CA*net 3, the first national optical internet	

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Year	Event	Major event
1998	CDA II and a ban on Net taxes are signed into US law (21 October)	
1998	US DoC enters into an agreement with the Internet Corporation for Assigned Numbers (ICANN) to establish a process for transitioning DNS from US Government management to industry (25 November)	
1998	San Francisco sites without off-city mirrors go offline as the city blacks out on 8 December	
1998	Chinese government puts Lin Hai on trial for "inciting the overthrow of state power" for providing 30000 email addresses to a US Internet magazine (December) [He is later sentenced to two years in jail]	
1998	Open source software comes of age	
1998	Technologies of the Year: E-Commerce, E-Auctions, Portals	
1998	Emerging Technologies: E-Trade, XML, Intrusion Detection	
1999	IBM becomes the first Corporate partner to be approved for Internet2 access	
1999	European Parliament proposes banning the caching of Web pages by ISPs	
1999	US State Court rules that domain names are property that may be garnished	
1999	MCI/Worldcom, the vBNS provider for NSF, begins upgrading the US backbone to 2.5Gbps	
1999	A forged Web page made to look like a Bloomberg financial news story raised shares of a small technology company by 31% on 7 April.	
1999	SETI@Home launches on 17 May and within four weeks its distributed Internet clients provide more computing power than the most powerful supercomputer of its time	X
1999	First large-scale Cyberwar takes place simultaneously with the war in Serbia/Kosovo	X
1999	Abilene, the Internet2 network, reaches across the Atlantic and connects to NORDUnet and SURFnet	
1999	The Web becomes the focal point of British politics as a list of MI6 agents is released on a UK Web site. Though forced to remove the list from the site, it was too late as the list had already been replicated across the Net. (15 May)	
1999	Activists Net-wide target the world's financial centers on 18 June, timed to coincide with the G8 Summit. Little actual impact is reported.	
1999	DoD issues a memo requiring all US military systems to connect via NIPRNET, and not directly to the Internet by 15 Dec 1999 (22 Aug)	
1999	ISOC approves the formation of the Internet Societal Task Force (ISTF). Vint Cerf serves as first chair	
1999	Free computers are all the rage (as long as you sign a long term contract for Net service)	
1999	Technologies of the Year: E-Trade, Online Banking, MP3	
1999	Emerging Technologies: Net-Cell Phones, Thin Computing, Embedded Computing	
2000	The US timekeeper (USNO) and a few other time services around the world report the new year as 19100 on 1 Jan	

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Year	Event	Major event
2000	A massive denial of service attack is launched against major web sites, including Yahoo, Amazon, and eBay in early February	X
2000	Web size estimates by NEC-RI and Inktomi surpass 1 billion indexable pages	X
2000	Internet2 backbone network deploys IPv6 (16 May)	
2000	Various domain name hijackings took place in late May and early June, including internet.com, bali.com, and web.net	
2000	After months of legal proceedings, the French court rules Yahoo! must block French users from accessing hate memorabilia in its auction site (Nov). Given its inability to provide such a block on the Internet, Yahoo! removes those auctions entirely (Jan 2001). The case is eventually thrown out (Feb 2003).	
2000	The European Commission contracts with a consortium of 30 national research networks for the development of Géant, Europe's new gigabit research network meant to enhance the current capability provided by TEN-155 (6 Nov)	
2000	Technologies of the Year: ASP, Napster	
2000	Emerging Technologies: Wireless devices, IPv6	
2001	The first live distributed musical – The Technophobe & The Madman – over Internet2 networks debuts on 20 Feb	
2001	VeriSign extends its multilingual domain testbed to encompass various European languages (26 Feb), and later the full Unicode character set (5 Apr) opening up most of the world's languages	
2001	Forwarding email in Australia becomes illegal with the passing of the Digital Agenda Act, as it is seen as a technical infringement of personal copyright (4 Mar)	
2001	High schools in five states (Michigan, Missouri, Oregon, Virginia, and Washington) become the first to gain Internet2 access	
2001	Napster keeps finding itself embroiled in litigation and is eventually forced to suspend service; it comes back later in the year as a subscription service	
2001	European Council finalises an international cybercrime treaty on 22 June and adopts it on 9 November. This is the first treaty addressing criminal offences committed over the Internet.	
2001	Afghanistan's Taliban bans Internet access country-wide, including from Government offices, in an attempt to control content (13 Jul)	
2001	Code Red worm and Sircam virus infiltrate thousands of web servers and email accounts, respectively, causing a spike in Internet bandwidth usage and security breaches (July)	
2001	A fire in a train tunnel running through Baltimore, Maryland seriously damages various fibre-optic cable bundles used by backbone providers, disrupting Internet traffic in the Mid-Atlantic states and creating a ripple effect across the US (18 Jul)	
2001	GÉANT, the pan-European Gigabit Research and Education Network, becomes operational (23 Oct), replacing the TEN-155 network which was closed down (30 Nov)	

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Year	Event	Major event
2001	First uncompressed real-time gigabit HDTV transmission across a wide-area IP network takes place on Internet2 (12 Nov).	
2001	Dutch SURFnet and Internet2's Abilene connect via gigabit ethernet (15 Nov)	
2001	Emerging Technologies: Grid Computing, P2P	
Spring and Summer 2001	Telecom bubble deflates and stocks tumble. Layoffs begin.	Label 11
2002	US ISP Association (USISPA) is created from the former CIX (11 Jan)	
2002	Global Terabit Research Network (GTRN) is formed composed of two OC-48 2.4GB circuits connecting Internet2 Abiline, CANARIE CA*net3, and GÉANT (18 Feb)	
2002	21st July: WorldCom files for bankruptcy, the 3rd largest bankruptcy in U.S. corporate history.	Label 11
2002	Abilene (Internet2) backbone deploys native IPv6 (5 Aug)	
2002	Internet2 now has 200 university, 60 corporate, and 40 affiliate members (2 Sep)	
2002	Having your own Blog becomes hip	
2002	A distributed denial of service (DDoS) attack struck the 13 DNS root servers knocking out all but 5 (21-23 Oct). Amidst national security concerns, VeriSign hastens a planned relocation of one of its two DNS root servers	
2002	The FBI teams up with Terras Lycos to disseminate virtual wanted posts across the Web portal's properties (11 Dec)	
2003	The first official Swiss online election takes place in Anières (7 Jan)	
2003	The SQL Slammer worm causes one of the largest and fastest spreading DDoS attacks ever. Taking roughly 10 minutes to spread worldwide, the worm took down 5 of the 13 DNS root servers along with tens of thousands of other servers, and impacted a multitude of systems ranging from (bank) ATM systems to air traffic control to emergency (911) systems (25 Jan). This is followed in August by the Sobig.F virus (19 Aug), the fastest spreading virus ever, and the Blaster (MSBlast) worm (11 Aug), another one of the most destructive worms ever	
2003	Flash mobs, organised over the Net, start in New York and quickly form in cities worldwide	
2003	The French Ministry of Culture bans the use of the word "e-mail" by government ministries, and adopts the use of the more French sounding "courriel" (Jul)	
2003	Last Abilene segment upgraded to 10Gbps (5 Nov)	
2004	For the first time, there are more instances of DNS root servers outside the US with the launch of an anycast instance of the RIPE NCC operated K-root server	
2004	Abiline, the Internet2 backbone, upgrade from 2.5Gbps to 10Gbps is completed (4 Feb)	
2004	Thefacebook launches (4 Feb)	Label 12

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Year	Event	Major event
2004	CERNET2, the first backbone IPv6 network in China, is launched by the China Education and Research Network (CERN) connecting 25 universities in 20 cities at speeds of 1-10Gbps (27 Dec)	
2004	Emerging Technologies: Social networking, Web mashups	
2005	Estonia offers Internet voting nationally for local elections	
2005	Pakistan suffers a near complete Internet outage as a submarine cable becomes defective (Jun)	
2005	Number of Internet users reaches 1 Billion (Oct)	X
2006	Zimbabwe looses most of its Internet access after its satellite connectivity is cut by the provider for non-payment	
2006	ICANN lifts price controls on .biz, .info, and .org domain names, after the same was done for .net in 2005, raising fears of tiered pricing where popular domains would cost more	
2006	First tweet is sent out by Jack Dorsey (21 Mar) – "just setting up my twttr"	
2006	The 6bone, an IPv6 testbed, is phased out after 10 years operation (6 Jun)	
2006	Internet2 connectivity begins switching from Abilene to its new network (Nov)	
2006	Internet connectivity to south-east Asia is severely limited after major fibre-optic lines are severely damaged by an earthquake in Taiwan and subsequent underwater mudslides (Dec)	
2006	Emerging Technologies: Cloud computing	
2007	Estonia offers the first online national parliamentary elections on 26-28 Feb	
2007	Internet2 traffic in the North-east US is disrupted on 1 May when a homeless man starts a fire under a Boston bridge causing a fibre break	
2007	Use of #hashtag proposed by Tweeter user number 1186, Chris Messina (23 Aug)	
2007	Internet2's Abilene network is retired (Sep) as the last connections are switched over to the new Level 3 network	
2007	Internet2 completes US East to West coast span of its 100GB/s network on 9 Oct	
2008	NASA successfully tests the first deep space communications network modelled on the Internet, using the Disruption-Tolerant Networking (DTN) software to transmit images to/from a science spacecraft approximately 20 million miles above Earth	X
2008	Google's crawler reaches 1 trillion pages, although only a fraction are indexed by the search engine. For comparison, Google's original index had 26 million pages in 1998, and reached 1 billion in 2000	
2008	The Middle East, India, and other parts of Africa and Asia see a major degradation in Internet service, including outages, after several undersea cables carrying Internet traffic to the region are cut within 1 week (Jan-Feb)	
2008	YouTube becomes unreachable for a couple of hours after Pakistan Telecom starts an unauthorised announcement of YouTube's subnet prefix (24 Feb)	
2009	Bitcoins start being minted	Label 13

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Year	Event	Major event
2009	US Department of Commerce relaxes control over ICANN, in favour of a multi-national oversight group	
2009	Twitter is asked by the US Government to delay planned maintenance of its service on 15 June as a result of heavy use by Iranian users during unrest in that country	
2009	Crowdfunding becomes a popular means of raising start-up funds; Kickstart founded on April 28	X
2009	Emerging Technologies: Location awareness	
2010	Astronaut T.J. Creamer inaugurates the new International Space Station direct link to the Internet (aka Crew Support LAN) with a tweet (22 Jan) – "Hello Twitterverse! We r now LIVE tweeting from the International Space Station – the 1st live tweet from Space! :) More soon, send your ?s"	
2010	Google announces on 22 January that along with 20+ other US companies, it had been the target of a cyberattack originating in China, and on 22 March stops censoring its services in China	
2010	Google+ service launches in public beta on 28 June; surpasses 10M users in Jul 2011, 100M in Feb 2012, and 400M in Sep 2012	
2010	Number of registered domain reach 200M (around August)	
2010	A BGP experiment between RIPE NCC and Duke U results in a partial Internet outage (27 Aug)	
2010	US Senate authorises US Dept. of Homeland Security to seize domains of sites suspected of piracy (Nov)	
2010	Myanmar is temporarily taken offline by a denial of service attack (Nov)	
2010	Photo-sharing sees a renewal with the launch of social-based services such as Pinterest and Instagram	
2011	LinkedIn reaches 100M users (Mar); surpasses 200M in Jan 2013	
2011	Egypt shuts down its last ISP on 31 Jan and remains offline for two days	
2011	Internet traffic in Lybia is significantly curtailed for several days in February	
2011	World IPv6 Day is 8 June	
2011	Number of Internet users reaches 2 Billion (Nov)	X
2012	ICANN begins accepting applications for new generic top-level domains (gTLDs) on 12 Jan	
2012	Facebook reaches 1 billion monthly active users (604M mobile) on 14 Sep @ 12:50pm PT, with 581M daily on average	X
2012	Amazon becomes the largest hosting location by number of web-facing computers (118k), knocking China Telecom from first place (116k)	
2012	World IPv6 Launch is 6 June	
2012	Minitel shuts down at the end of June	

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Year	Event	Major event
2012	GoDaddy service goes down, making millions of sites inaccessible for several hours (10 Sep)	
2012	Twitter surpasses 200M active users (Dec), and 500M tweets per day (Oct)	
2012	NASA's Curiosity Rover checks-in on FourSquare from Mars (3 Oct)	
2012	Syria is disconnected from the Internet for two days (29 Nov - 1 Dec)	
2012	"Gangnam Style" becomes the first YouTube video to reach 1 billion views (21 Dec)	X
2013	Netflix and YouTube account for over 50% of Internet traffic measured by bytes	
2013	US National Security Agency (NSA) is revealed to be collecting considerable more Internet data than previously thought, including encrypted information from major Internet sites	
2013	The number of Internet hosts surpass 1 billion	X
2014	Most of the Internet traffic in China is redirected to US-based Dynamic Internet Technology for over an hour (21 Jan)	
2014	.py ccTLD hacked – full whois registry data leaked and domains redirected (e.g., google.com.py) (20 Feb)	
2014	The number of Web servers surpass 1 billion	
2014	After an EU court ruling requiring Google to honour "requests to be forgotten", 12000 requests are submitted in the first day (30 May)	
2014	Many networks are taken offline due to a Verizon glitch introducing thousands of new prefixes into the global routing table, causing popular but unpatched Cisco routers to reach their 512000 limit and crash (12 Aug)	
2015	A Georgian scavenging for copper cuts off much of the Internet in neighbouring Armenia when her spade slices a buried cable (28 Mar)	
2015	Out of 100 billion monthly Google searches, those from mobile devices surpass desktops for the first time	X
2015	1 billion users (1 in 7 people on Earth) access Facebook on a single day (24 Aug)	Label 14
2015	WordPress powers 25% of web sites as of early November	
2015	Most of the internal Internet connectivity in Azerbaijan is lost as a result of a fire in a telecommunications facility (16 Nov)	
2016	Internet Society celebrates 25th anniversary (1 Jan)	
2016	United Nations Human Rights Council adopts a resolution on the promotion, protection and enjoyment of human rights on the Internet (27 Jun)	
2016	A California District Court Judge grants a motion for what is thought to be the first permitted serving of a lawsuit via Twitter (30 Sep)	
2016	Yahoo discloses 500 million accounts compromised in 2014 (22 Sep) and that 1 billion accounts were compromised in Aug 2013 (14 Dec)	
2016	DDoS attacks wreak havoc across the Internet with some topping over 1Tbps in bandwidth and powered by over 150000 hacked Internet devices	

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Year	Event	Major event
2016	Several prominent Internet sites become unreachable as domain infrastructure provider Dyn is knocked offline by a DDoS attack (21 Oct)	
2016	IPv6 reaches 10% deployment globally, and becomes the dominant (i.e. greater than 50%) Internet protocol for US mobile networks	
2016	Coordination and management of the Internet's unique identifiers transition to the private sector as the IANA contract between ICANN and the US Dept of Commerce's NTIA expires (1 Oct)	
2016	Annual global IP traffic surpasses 1 zettabyte	X
2017	IETF enters into an agreement with the National Library of Sweden for archival of RFC series in NLS' bunker (16 Jan)	

Table A7: Timeline of landline telephones [Stritof, 2004, ETHW.org, 2015a, Telia Company, 2018, Wireless History Foundation, 2018, Nonnenmacher, 2001]

Year	Event	Major event
Throughout history	Voice telegraphs used hundreds of years BC through the Middle Ages and in the Canary Islands today.	
1200 BC	Homer talks about signal fires in the Iliad.	
700 BC to 300 AD	Carrier pigeons used in Olympic games	
1588	Arrival of the Spanish Armada announced by signal fires	
1667	Robert Hooke creates an acoustic string telephone that conveys sounds over a taut extended wire by mechanical vibrations.	
c. 1800	A line of canon from Buffalo to NYC used to announce Gov. DeWitt Clinton's inaugural trip through the Erie Canal. It took 80 minutes.	
1791	The Chappe brothers, in France, were in their teens and were going to schools some distance apart but visible to each other. They obtained permission to set up a signalling system so they could send messages to each other. Their semaphore system consisted of movable arms on a pole whose positions denoted letters of the alphabet.	
1793	The Chappe brothers established the first commercial semaphore system between two locations near Paris. Napoleon thought this was a great idea. Soon there were semaphore signalling systems covering the main cities of France. Semaphore signalling spread to Italy, Germany and Russia. Thousands of men were employed manning the stations. Speed: about 15 characters per minute. Code books came into play so that whole sentences could be represented by a few characters. Semaphores were not very successful in England because of the fog and smog caused by the Industrial Revolution. Claude Chappe headed France's system for 30 years and then was "retired" when a new administration came into power. There were semaphore systems in the U.S., especially from Martha's Vineyard (an island near Cape Cod) and Boston, reporting to Boston's Custom House on the movement of sailing ships. This was also true around New York City and San Francisco. Samuel F.B. Morse, the inventor of the electric telegraph, reportedly saw the semaphore system in operation in Europe. The last operational semaphore system went out of business in 1860. It was located in Algeria.	
1837	Cooke and Wheatstone obtain a patent on telegraph in England. Morse publicly demonstrates his telegraph.	X
1838	Morse's Electro-Magnetic Telegraph patent approved.	
1840	Congress was requested to provide funding for a semaphore system running from NYC to New Orleans. Samuel Morse, it is said, advised against funding of this system because of his work on developing the electric telegraph.	
1843	FAX invented by the Scotch physicist Alexander Bain.	

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Year	Event	Major event
1844	Morse demonstrates the electric telegraph. Samuel F.B. Morse demonstrates his telegraph by sending a message to Baltimore from the chambers of the Supreme Court in Washington, DC. The message, "What hath God wrought?", marks the beginning of a new era in communication.	X
1844	Morse's first telegraph line between Washington and Baltimore opens in May.	
1844	Innocenzo Manzetti first suggests the idea of an electric "speaking telegraph", or telephone.	X
1846	First commercial telegraph line completed. The Magnetic Telegraph Company's lines ran from New York to Washington.	X
1846	House's Printing Telegraph patent approved.	
1847	3rd March: Birth of Alexander Graham Bell, Edinburgh, Scotland.	
1848	Associated Press formed to pool telegraph traffic.	
1849	Antonio Meucci demonstrates a communicating device to individuals in Havana. It is disputed if this is an electromagnetic telephone, but is said to involve direct transmission of electricity into the user's body.	X
1849	Alexander Bain's Electro-Chemical patent approved.	
1850s	Telegraph expansion in the U.S. and into Europe: The electrical telegraph is broadly introduced in Europe during the 1850s. It is based on a number of discoveries and inventions in the use of electricity. The telegraph implies a revolutionary improvement in the transport of written messages. The telegraph is often linked to the building of railway transportation networks.	X
1851	Telegraph first used to coordinate train departures.	
1851	There are 51 telegraph companies in operation	
1851	Hiram Sibley and associates incorporate 'New York and Mississippi Valley Printing Telegraph Company'. This later became Western Union.	
1854	Charles Bourseul publishes a description of a make-and-break telephone transmitter and receiver in L'Illustration, (Paris) but does not construct a working instrument.	X
1854	Meucci demonstrates an electric voice-operated device in New York, but it is not clear what kind of device he demonstrated.	X
1856	Western Union formed by six men from Rochester, N.Y., including the 'New York and Mississippi Valley Printing Telegraph Company'. They start an acquisition spree.	
1857	Treaty of Six Nations is signed, creating a national cartel in the U.S.	
1858	Burglar Alarm - Edwin T. Holmes of Boston begins to sell electric burglar alarms. Later, his workshop will be used by Alexander Graham Bell as the young Bell pursues his invention of the telephone. Holmes will be the first person to have a home telephone.	
1859	First transatlantic telegraph cable attempt is laid from Newfoundland to Valentia, Ireland. Fails after 23 days, having been used to send a total of 4359 words. Total cost of laying the line was $1.2 million.	X

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Year	Event	Major event
1860s	Sea cables improve international telegraph links: The progress in undersea cable development makes it possible for the telegraph to cross oceans in order to link Europe with North America and other continents. The first stable transatlantic cable is laid by the giant British steamer Great Eastern. Two more cables follow the same year through a repair of a previous broken cable and a successful parallel French project.	X
1860	Johann Philipp Reis of Germany demonstrates a make-and-break transmitter after the design of Bourseul and a knitting-needle receiver. Witnesses said they heard human voices being transmitted.	X
1861	Johann Philipp Reis transfers voice electrically over a distance of 340 feet with his Reis telephone. To prove that speech can be recognised successfully at the receiving end, he uses the phrase "The horse does not eat cucumber salad" as an example because this phrase is hard to understand acoustically in German.	X
1861	First transcontinental telegraph completed in the United States, connecting both coasts. There are now 2250 telegraph offices in operation in the U.S.	X
1864	In an attempt to give his musical automaton a voice, Innocenzo Manzetti invents the 'speaking telegraph'. He shows no interest in patenting his device, but it is reported in newspapers.	X
1865	Maxwell mathematically predicts the propagation of electromagnetic waves through space.	
1865	Meucci reads of Manzetti's invention and writes to the editors of two newspapers claiming priority and quoting his first experiment in 1849. He writes "I do not wish to deny Mr. Manzetti his invention, I only wish to observe that two thoughts could be found to contain the same discovery, and that by uniting the two ideas one can more easily reach the certainty about a thing this important". If he reads Meucci's offer of collaboration, Manzetti does not respond.	X
1866	First successful transatlantic telegraph line laid on the 27th of July. Prior to the cable, sending messages between the United States and Europe took 11 days. This allows uninterrupted transatlantic communications.	X
1866	Western Union merges with major remaining rivals.	
1867	Stock ticker service inaugurated.	X
1869	The Great Northern Telegraph Co, a privately owned company, is established in Copenhagen by Carl Frederik Tietgen to provide telegraph connections across the North Sea between the Nordic countries and England and also across the Baltic to Russia. GNT establishes a cable from Grisslehamn in Sweden to Finland providing a direct connection to Russia. The telegraph cable is terminated at Uusikaupunki (Nystad) and GNT sets up its telegraph gateway there.	X

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Table A7 – continued from previous page

Year	Event	Major event
1870s	The telephone starts to compete with the telegraph: Many scientists and inventors work on the problem of transmitting voice signals by electricity over wires. Several claim to be first, but the first patent is awarded to Alexander Graham Bell in the USA in 1876. The news of the invention spreads very quickly over the world and experimental installation are made in many places during the end of the 1870s. The electrical signals are much weaker than in the case of the telegraph, so the telephone remains a relatively short range means of communication in relation to the telegraph for about four decades. The telephone is initially not regarded as a serious competitor by the telegraph operators.	X
1870	Western Union introduces the money order service.	
1870	Thomas Edison invents multiplex telegraphy.	
1871	Meucci files a patent caveat (a statement of intention to file a patent application) for a Sound Telegraph, but it does not describe an electromagnetic telephone.	X
1871	1st April: Bell arrived in Boston to start his work in the teaching of the deaf.	
1872	Professor Vanderwyde demonstrates Reis's telephone in New York.	
1872	Western Union buys the telegraph equipment manufacturing firm, Gray & Barton (founded by Elisha Gray), and renames it Western Electric.	
1873	July: Thomas Edison notes varying resistance in carbon grains due to pressure, and builds a rheostat based on the principle but abandons it because of its sensitivity to vibration.	
1874	May: Gray invents an electromagnet device for transmitting musical tones. Some of his receivers use a metallic diaphragm.	X
1874	July: Alexander Graham Bell conceives the theoretical concept for the telephone while vacationing at his parents' farm near Brantford, Canada. Alexander Melville Bell records notes of his son's conversation in his personal journal.	X
1874	29th December: Gray demonstrates his musical tones device and transmits "familiar melodies through telegraph wire" at the Presbyterian Church in Highland Park, Illinois.	X
1875	2nd June: Bell's theory of the telephone confirmed by experiment.	X
1875	4th May: Bell conceives of using varying resistance in a wire conducting electric current to create a varying current amplitude.	X
1875	First words transmitted by telephone.	X
1875	2nd June: Bell transmits the sound of a plucked steel reed using electromagnet instruments.	X
1875	1st July: Bell uses a bi-directional "gallows" telephone that was able to transmit "indistinct but voice-like sounds" but not clear speech. Both the transmitter and the receiver were identical membrane electromagnet instruments.	X
1875	November: Thomas Edison experiments with acoustic telegraphy and, in November, builds an electro-dynamic receiver but does not exploit it.	X
1876	11th February: Elisha Gray invents a liquid transmitter for use with a telephone, but he did not make one.	X

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Year	Event	Major event
1876	14th February, about 9:30 am: Gray or his lawyer brings Gray's patent caveat for the telephone to the Washington, D.C. Patent Office (a caveat was a notice of intention to file a patent application. It was like a patent application, but without a request for examination, for the purpose of notifying the patent office of a possible invention in process).	X
1876	14th February, about 11:30 am: Bell's lawyer brings to the same patent office Bell's patent application for the telephone. Bell's lawyer requests that it be registered immediately in the cash receipts blotter.	X
1876	14th February, about 1:30 pm: Approximately two hours later Elisha Gray's patent caveat is registered in the cash blotter. Although his caveat was not a full application, Gray could have converted it into a patent application and contested Bell's priority, but did not do so because of advice from his lawyer and his involvement with acoustic telegraphy. Over 600 patent suits filed during the next 11 years. Settled in Bell's favour. The result was that the patent was awarded to Bell. Bell offers his patent to Western Union for $100000.	X
1876	7th March: Bell's U.S. Patent, No. 174465 for the telephone is granted.	X
1876	10th March: Bell first successfully transmits speech, saying "Mr. Watson, come here! I want to see you!" using a liquid transmitter as described in Gray's caveat, and Bell's own electromagnetic receiver.	X
1876	16th May: Thomas Edison files first patent application for acoustic telegraphy for which U.S. patent 182996 was granted 10th October, 1876.	
1876	25th June: Bell exhibits his telephone at the Centennial Exposition in Philadelphia, where it draws enthusiastic reactions from Emperor Dom Pedro II of Brazil and Lord Kelvin, attracting the attention of the press and resulting in the first announcements of the invention to the general public.	
1876	10th August: Alexander Graham Bell makes the world's first long-distance telephone call, over a distance of about 6 miles, between Brantford and Paris, Ontario, Canada.	X
1876	October: Edison tests his first carbon microphone.	X
9 October 1876	Bell makes the first two-way long-distance telephone call between Cambridge and Boston, Massachusetts.	X

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Table A7 – continued from previous page

Year	Event	Major event
1876	Response from Western Union to Alexander Graham Bell's original proposal to sell patent to them for \$100000 in 1876: In 1876, Alexander Graham Bell and his financial backer, Gardiner G. Hubbard, offered Bell's brand new patent (No. 174465) to the Telegraph Company - the ancestor of Western Union. The President of the Telegraph Company, Chauncey M. DePew, appointed a committee to investigate the offer. The committee report has often been quoted. It reads in part: "The Telephone purports to transmit the speaking voice over telegraph wires. We found that the voice is very weak and indistinct, and grows even weaker when long wires are used between the transmitter and receiver. Technically, we do not see that this device will be ever capable of sending recognizable speech over a distance of several miles." "Messer Hubbard and Bell want to install one of their "telephone devices" in every city. The idea is idiotic on the face of it. Furthermore, why would any person want to use this ungainly and impractical device when he can send a messenger to the telegraph office and have a clear written message sent to any large city in the United States?" "The electricians of our company have developed all the significant improvements in the telegraph art to date, and we see no reason why a group of outsiders, with extravagant and impractical ideas, should be entertained, when they have not the slightest idea of the true problems involved. Mr. G.G. Hubbard's fanciful predictions, while they sound rosy, are based on wild-eyed imagination and lack of understanding of the technical and economic facts of the situation, and a posture of ignoring the obvious limitations of his device, which is hardly more than a toy... ." "In view of these facts, we feel that Mr. G.G. Hubbard's request for \$100000 of the sale of this patent is utterly unreasonable, since this device is inherently of no use to us. We do not recommend its purchase." The amusing thing about this letter, in retrospect, is that Bell obtained controlling interest in Western Union by 1882!	
1876	7th March: The first telephone patent, No. 174465 was issued to Alexander Graham Bell.	
1876	10th March: First complete sentence of speech transmitted by telephone in Boston.	
1876	25th June: Bell exhibited the telephone to the judges at the Centennial Exposition, Philadelphia.	
1876	9th October: Bell conducted the first successful experimental two-way talk over the telephone between Boston and Cambridgeport, Mass., distance of 2 miles.	
1876	First conversation by overhead line, 2 miles-Boston to Cambridgeport.	
1876	Edison invents the electric motor and the phonograph.	
1876	Hungarian Tivadar Puskás invents the telephone switchboard exchange (later working with Edison).	X
1877	20th January: Edison "first [succeeds] in transmitting over wires many articulated sentences" using carbon granules as a pressure-sensitive varying resistance under the pressure of a diaphragm.	X

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Table A7 – continued from previous page

Year	Event	Major event
1877	30th January: Bell's U.S. Patent No. 186787 is granted for an electromagnetic telephone using permanent magnets, iron diaphragms, and a call bell.	X
1877	4th March: Emile Berliner invents a microphone based on "loose contact" between two metal electrodes, an improvement on Reis' Telephone, and in April 1877 files a caveat of an invention in process.	X
1877	April: A telephone line connects the workshop of Charles Williams, Jr., located in Boston, to his house in Somerville, Massachusetts at 109 Court Street in Boston, where Alexander Graham Bell and Thomas Watson had previously experimented with their telephone. The telephones became No. 1 and 2 in the Bell Telephone Company.	
1877	27th April: Edison files telephone patent applications. U.S. patents (Nos. 474230, 474231 and 474232) were awarded to Edison in 1892 over the competing claims of Alexander Graham Bell, Emile Berliner, Elisha Gray, Amos Dolbear, J.W. McDonagh, G.B. Richmond, W.L.W. Voeker, J.H. Irwin and Francis Blake Jr. Edison's carbon granules transmitter and Bell's electromagnetic receiver are used, with improvements, by the Bell system for many decades thereafter.	X
1877	4th June: Emile Berliner files telephone patent application that includes a carbon microphone transmitter.	X
1877	9th July: The Bell Telephone Company, a common law joint-stock company, is organised by Alexander Graham Bell's future father-in-law Gardiner Greene Hubbard, a lawyer who becomes its first president. Alexander Graham Bell acts as "electrician" and Thomas Watson as "superintendent".	X
1877	6th October: The Scientific American publishes the invention from Bell - at that time still without a ringer.	X
1877	25th October: The article in the Scientific American is discussed at the Telegraphenamt in Berlin	X
1877	12th November: The first commercial telephone company enters telephone business in Friedrichsberg close to Berlin using the Siemens pipe as ringer and telephone devices build by Siemens.	X
1877	1st December: Western Union enters the telephone business using Edison's superior carbon microphone transmitter.	X
1877	The first experimental Telephone Exchange in Boston.	X
1878	28th January: The first commercial North American telephone exchange is opened in New Haven, Connecticut, with 21 listings.	X
1878	4th February: Edison demonstrates the telephone between Menlo Park, New Jersey and Philadelphia, a distance of 210 kilometres (130 miles)	

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Table A7 – continued from previous page

Year	Event	Major event
1878	14th June: The Telephone Company (Bell's Patents) Ltd. is registered in London. Opened in London on 21 August 1879, it is Europe's first telephone exchange, followed a couple of weeks later by one in Manchester.	
1878	12th September: The Bell Telephone Company sues Western Union for infringing Bell's patents.	
1878	The first Australian telephone trials were made between Semaphore and Kapunda (and later Adelaide and Port Adelaide) in South Australia.	
Early 1879	The Bell Telephone Company is near bankruptcy and desperate to get a transmitter to equal Edison's carbon transmitter.	
1879	17th February: Bell Telephone merges with the New England Telephone Company to form the National Bell Telephone Company. Theodore Vail takes over operations.	
1879	Francis Blake invents a carbon transmitter similar to Edison's that saves the Bell company from extinction.	X
1879	2nd August: The Edison Telephone Company of London Ltd, registered. Opened in London 6 September 1879.	
1879	10th September: Connolly and McTighe patent a "dial" telephone exchange (limited in the number of lines to the number of positions on the dial).	
1879	The International Bell Telephone Company (IBTC) of Brussels, Belgium was founded by Bell Telephone Company president Gardiner Greene Hubbard, initially to sell imported telephones and switchboards in Continental Europe. International Bell rapidly evolved into an important European telephone service provider and manufacturer, with major operations in several countries.	X
1880	19th February: The photophone, also called a radiophone, is invented jointly by Alexander Graham Bell and Charles Sumner Tainter at Bell's Volta Laboratory. The device allowed for the transmission of sound on a beam of light.	
1880	20th March: National Bell Telephone merges with others to form the American Bell Telephone Company.	X
1880	1st April: World's first wireless telephone call on Bell and Tainter's photophone (distant precursor to fibre-optic communications) from the Franklin School in Washington, D.C. to the window of Bell's laboratory, 213 metres away.	
1880	Bell spoke over a 1300-ft beam of light using his patented Photophone equipment.	
1880	30872 Bell telephone stations in the United States. Conversation by overhead line, 45 miles-Boston to Providence.	
1881	1st July: The world's first international telephone call is made between St. Stephen, New Brunswick, Canada, and Calais, Maine, United States.	X
1881	11th October: The Sydney telephone exchange opened with 12 subscribers.	
1881	Alexander Graham Bell patents the metallic, or two-wire, circuit.	

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Year	Event	Major event
1881	Mr. Eckert who ran a telephone company in Cincinnati said he preferred the use of females to males as operators. “Their service is much superior to that of men or boys. They are much steadier, do not drink beer nor use profanity, and are always on hand”.	
1881	Bell Telephone company purchases Western Electric Company.	X
1881	Conversation by underground cable, 3/4 mile.	
1882	Bell has controlling interest in Western Union and Western Electric.	X
1882	A telephone company—an American Bell Telephone Company affiliate—is set up in Mexico City.	
1883	14th May: The Adelaide exchange was opened, with 48 subscribers.	
1883	7th September: The Port Adelaide exchange was opened, with 21 subscribers.	
1884	Hard-drawn copper wire begins to replace iron wires.	
1884	Paul Nipkow obtains a patent in Germany for TV, using a selenium cell and a mechanical scanning disk.	X
1884	4th September: Opening of telephone service between Boston and New York, 235 miles. First long distance conversation by overhead line (hard-drawn copper).	X
1885	3rd March: The American Telephone & Telegraph Company (AT&T) is incorporated as the long-distance division of American Bell Telephone Company. It will become the head of the Bell System on the last day of 1899.	X
1885	Theodore Vail becomes President of AT&T. Leaves in 1887 to go to South America to install electric traction systems.	
1886	Gilliland’s Automatic circuit changer is put into service between Worcester and Leicester featuring the first operator dialling allowing one operator to run two exchanges.	
1887	13th January: The Government of the United States moves to annul the master patent issued to Alexander Graham Bell on the grounds of fraud and misrepresentation. The case, known as the ‘Government Case’, is later dropped after it was revealed that the U.S. Attorney General, Augustus Hill Garland had been given millions of dollars of stock in the company trying to unseat Bell’s telephone patent.	
1887	Tivadar Puskás introduced the multiplex switchboard, that had an epochal significance in the further development of telephone exchange.	X
1887	Heinrich Hertz shows that electromagnetic waves exist.	X
1888	Telephone patent court cases are confirmed by the Supreme Court	
1888	Heinrich Hertz produces radio waves.	X
1889	AT&T becomes the overall holding company for all the Bell companies.	
1889	Almon B. Strowger invents a switch that has line contacts in circular rows inside a cylinder. Controlled by push-buttons on telephone.	X

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Year	Event	Major event
1889	2nd November: A.G. Smith patents a telegraph switch which provides for trunks between groups of selectors allowing for the first time, fewer trunks than there are lines, and automatic selection of an idle trunk.	X
1890	Herman Hollerith gets a contract for processing the 1900 census data using punched cards. His firm was eventually named IBM in 1924.	
1890	211503 Bell telephone stations.	
1891	Twisted pairs incorporated into telephone lines by John J. Carty.	
1891	10th March: Almon Strowger, the St. Louis undertaker, became upset on finding that the wife of a competitor was a telephone operator who made his line busy and transferred calls meant for him to her husband. "Necessity is the mother of invention" so Strowger developed the dial telephone system to get the operator out of the system. The invention he patents is a 1000 line switch using a disc bank having ten concentric rows of line contacts (the Strowger switch), which provides the first Automatic telephone exchange. This is not used commercially. Formation of Strowger Automatic Telephone Exchange to manufacture step-by-step central office equipment (which is now owned by GTE).	X
1891	30th October: The independent Strowger Automatic Telephone Exchange Company is formed.	
1892	3rd May: Thomas Edison awarded patents for the carbon microphone based on applications lodged in 1877.	X
1892	18th October: Opening of telephone service between New York and Chicago (950 miles).	X
1892	3rd November: The first Strowger switch goes into operation in LaPorte, Indiana with 75 subscribers and capacity for 99.	
1892	18th October: Opening of long distance telephone service, New York to Chicago, 950 miles.	
1892	Conversation by overhead line, 900 miles-New York to Chicago.	
1892	First commercial Strowger installation; LaPorte, Indiana, USA. Used switcher with 100 line disc-type banks.	
1893	An early form of broadcasting was started in Budapest over 220 miles of telephone wires serving 6000 subscribers who could listen at regular schedules to music, news, stock market prices, poetry readings and lectures.	
1894	30th January: The second fundamental Bell patent for the telephone expires; period of intense competition begins with independent telephone companies established, and independent manufacturing companies (Stromberg-Carlson in 1894 and Kellogg Switchboard & Supply Company in 1897).	
1894	Invention of gear-driven switch with "zither" (piano wire) line banks. Not used commercially. 200-line "zither" board with ratchet drive installed at LaPorte, Indiana, USA.	
1895	Guglielmo Marconi invented the radio.	X

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Year	Event	Major event
1895	Third installation at LaPorte, Indiana. Earliest use of switch with semi-cylindrical bank and shaft with vertical and rotary motions. Invention of earliest dial-type calling device.	
1896	Invention of selector trunking; first use of dial telephones in large exchange (Augusta, Georgia, USA).	
1896	Marconi patents wireless telegraph.	X
1898	Earliest use of relays for switch control instead of direct operation of magnets over line wires. First die cast switch frame.	
1899	30th December: American Bell Telephone Company is purchased by its own long-distance subsidiary, American Telephone and Telegraph (AT&T) to bypass state regulations limiting capitalisation. AT&T assumes leadership role of the Bell System.	
1899	Strowger Automatic goes abroad (Berlin, Germany). Earliest use of automatic trunk selection with busy test.	
1899	Loading Coil theory developed independently by Michael Pupin and George Campbell.	
1900	John J. Carty, Chief Engineer of NY Tel (and later AT&T), installs loading coils, invented by Michael Pupin, to extend range and utilises open wire transposition to reduce crosstalk an inductive pickup from ac transmission lines. AT&T paid Pupin $255000 for the use of his patent. There are now about 20000 telcos in business. There are now 856000 telephones in service.	
1900	676733 Bell telephone stations owned and connected.	
1900	Basic trunking principles established for large exchanges. Bank terminals moulded in plaster of Paris.	
1900	25th December: John W. Atkins, the manager at International Ocean Telegraph Company (IOTC), a subsidiary of Western Union Telegraph Company made the first international telephone call over telegraph cable at 09:55am from his office in Key West to Havana, Cuba. Atkins was reported in the Florida Times Union and Citizen as saying, “For a long time there was no sound, except the roar heard at night sometimes, caused by electric light current”. He continued calling Cuba and finally came back the words, clear and distinct: “I don’t understand you”.	Label 1
1901	27th February: United States Court of Appeal declares void Emile Berliner’s patent for a telephone transmitter used by the Bell telephone system	
1901	Formation of Automatic Electric Company to take over Strowger Automatic Telephone Exchange. Installation at Fall River, Mass., used line banks with fibre insulators and aluminium fillers. First use of slip multiple.	
1901	Guglielmo Marconi transmits first transatlantic radio message (from Cape Cod) on 12th December.	Label 1
1902	First conversation by long distance underground cable, 10 miles - New York to Newark.	

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Year	Event	Major event
1902	First installation in Chicago begun. Earliest use of measured service in automatic exchanges.	
1902	Poulsen-Arc Radio Transmitter invented.	
1902	The first Australian interstate calls between Mt Gambier and Nelson.	
1903	Large Strowger installations placed in service in Grand Rapids, Dayton, Akron, Columbus.	
1903	AIEE Committee on Telegraphy and Telephony formed.	
1904	First use of multi-office trunking, and connections between automatic and manual offices (Los Angeles, Califonia).	
1904	John Ambrose Fleming invents the two-element "Fleming Valve".	
1905	Earliest extended use of party lines and reverting calls. First system using common battery talking (South Bend, Indiana).	
1905	Marconi patents his directive horizontal antenna.	
1906	Lee deForest invents the vacuum tube.	Label 2
1906	Conversation by underground cable, 90 miles-New York to Philadelphia.	
1906	Invention of Keith Line Switch, resulting in enormous reduction in cost of automatic boards. First used at Wilmington, Delaware.	Label 2
1906	Dr. Lee de Forest reads a paper before an AIEE meeting on the Audion, first of the vacuum tubes that would make long distance radiotelephony possible. Reginald Fessenden broadcasts Christmas Carols on Christmas Eve from Brant Rock, MA.	X
1907	States start to regulate telcos. Mississippi was among the first. The idea of regulation goes back several centuries, when in England, innkeepers were required to post their charges to prevent gouging. "Common carrier" regulation refers to government approval of tariffs filed by railroads, truck lines, telcos, etc which provide the terms and conditions whereby the public can make use of their services.	
1907	Theodore Vail returns as President of AT&T (and Western Union). He is responsible for the concept of "end-to-end" service that guided AT&T and other telcos in providing the C.O., transmission systems, and CPE that lasted until the Carterphone and Specialized Common Carrier Decisions.	
1907	First installation in Canada (Edmonton, Alta.). Invention of small dial and two-wire system eliminating ground at subscribers station.	
1907	The world's first transatlantic commercial wireless services is established by Marconi with stations at Clifden, Ireland and Glace Bay, Nova Scotia.	
1908	AT&T gains control of Western Union. Divests itself of Western Union in 1913.	
1908	First two-wire system (large dial) installed at Pontiac, Illinois. Earliest use of automatic, intermittent ringing. Installation at Lansing, Michigan. Features use of small dial, secondary line switch, and 200-point selectors and connectors.	
1909	Western Union and AT&T are closely locked.	

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Year	Event	Major event
1909	Invention of out-going secondary line switch, resulting in economy of inter-office trunks. First used at San Francisco.	
1909	Marconi shares the Nobel Prize in Physics, with Karl Ferdinand Braun for their work in the development of wireless telegraphy.	
1910	Peter DeBye in Holland, develops theory for optical waveguides. He was a few years ahead of his time. Interstate Commerce Commission starts to regulate telcos.	
1910	The Mann-Elkins Act enacted, putting interstate communications under the purview of the Interstate Commerce commission (ICC)	
1910	5142692 Bell telephone stations owned and connected.	
1910	Strowger system introduced in Hawaii and Cuba. Earliest use of dialling over toll lines. Introduction of revertive ringing tone.	
1910	The first commercial radios are sold by Lee de Forest's Radio Telephone Company.	
1911	Conversation by overhead line: 2100 miles, from New York to Denver.	
1911	Formation of Automatic Telephone Manufacturing Co., Ltd. For production of Strowger system in England.	
1911	Using loading coils properly spaced in the line, the transmission distance for telephone reaches from New York to Denver.	
1912	First Strowger installation in England (Epsom Official Switch).	
1913	The Kingsbury Agreement. Mr. Kingsbury was an AT&T vice president. In his famous letter to the U.S. Government, AT&T agrees to divest its holdings of Western Union, stop acquisition of other telcos, and permit other telcos to interconnect.	
1913	The Kingsbury Commitment precludes unapproved expansion, and permits connections to network.	
1913	The U.S. Justice Department filed its first antitrust suit against Bell, charging an unlawful combination to monopolise transmission of telephone service in the Pacific Northwest.	
1913	Conversation by overhead line: 2600 miles, from New York to Salt Lake City. Conversation by underground cable: 455 miles, from Boston to Washington.	
1913	Strowger system introduced in Australia and New Zealand. Development of key-type impulse sender, and Simplex dialling on toll lines.	
1914	Underground cables link Boston, NYC and Washington.	
1914	26th February: Boston-Washington underground telephone cable placed in commercial service.	
1914	Automatic Switches used as traffic distributors in manual exchanges (Indianapolis, Indiana and Defiance, Ohio).	
1914	The last pole of the transcontinental telephone line is placed in Wendover, Utah, on the Nevada-Utah state line.	

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Year	Event	Major event
1915	E.T. Whitaker develops the sampling theorem that forms the basis of today's PCM and TCM technologies.	X
1915	16th January: The first automatic Panel exchange was installed at the Mulberry Central Office in Newark, New Jersey; but was a semi-automatic system using non-dial telephones.	
1915	25th January: First U.S. transcontinental telephone call (3600 miles), with Thomas Augustus Watson at 333 Grant Avenue in San Francisco receiving a call from Alexander Graham Bell at 15 Dey Street in New York City, facilitated by Harold Arnold's newly invented vacuum tube amplifier. In opening the service at 4pm, EST, Bell, in New York, repeated his famous first telephone sentence to his former assistant, Mr.Watson, who was in San Francisco, "Mr. Watson, come here, I want you". Watson replied, "If you want me, it will take me almost a week to get there".	Label 3
1915	21st October: First transmission of speech across the Atlantic by radiotelephone, from Arlington, Va. to Paris, France.	Label 3
1915	First conversation by transcontinental line, 3650 miles-Boston to San Francisco. Speed transmitted for the first time by radio telephone from Arlington, Va., across the continent to San Francisco, over the Pacific to the Hawaiian Islands, and across the Atlantic to Paris.	X
1915	Development of modern covered switch with horizontal relays used at St. Paul and Minneapolis. First use of cast iron switch frame at Hazelton, Pennsylvania.	
1916	Earliest community automatic exchange network installed in Wisconsin.	
1917	Rapid expansion in the use of private automatic branch exchanges. Development of remote alarm equipment for unattended exchanges.	
1918	First installation of carrier circuits, based on work by George Campbell.	Label 3
1918	First installation using rotary primary line switches (Elyria, Ohio).	
1918	Edwin Armstrong develops a receiving circuit - the superheterodyne.	
1919	Radio Corporation of America (RCA) is formed.	
1919	The first rotary dial telephones using Strowger boards installed in the Bell System in Norfolk, Virginia. Telephones that lacked dials and touch-tone pads were no longer made by the Bell System after 1978.	X
1919	AT&T conducts more than 4000 measurements of people's heads to gauge the best dimensions of standard headsets so that callers' lips would be near the microphone when holding handsets up to their ears.	
1920	Bell introduces its own step-by-step offices that were previously acquired from Automatic Electric. G. Valensi develops the time domain multiplexing concept.	
1920	16th July: World's first radiotelephone service, between Los Angeles and Santa Catalina Island, opened to the public.	X
1920	11795747 Bell telephone stations owned and connected.	

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Year	Event	Major event
1920	Beginning of wide-spread adoption of Strowger equipment for metropolitan areas both in the U.S. and abroad. First installation of call-indicator equipment for automatic-manual connections in multi-office areas.	
1920	2nd November: the first regular commercial radio broadcasts begin when AM station KDKA of Pittsburgh delivers results of the Harding-Cox election to its listeners. Radio experiences immediate success; by the end of 1922, 563 other licenced stations will join KDKA.	X
1921	The Willis-Graham Act allows telcos to merge with permission of the States and the Interstate Commerce Commission.	
1921	11th April: Opening of deep sea cable: 115 miles, Key West, Florida, to Havana, Cuba. Followed by first conversation between Havana, Cuba, and Catalina Island by submarine cable, overhead and underground lines and radio telephone-distance 5500 miles. Extension of Boston - Philadelphia cable to Pittsburgh - total distance 621 miles. President Harding's inaugural address delivered by loud speaker to more than 100000 people. Armistice Bay exercises at burial of unknown soldier delivered by means of Bell loud speaker and long lines to more than 150000 people in Arlington, Va., New York and San Francisco.	
1921	Wirephoto - The first electronically-transmitted photograph is sent by Western Union. The idea for a facsimile transmission was first proposed by Scottish clockmaker Alexander Bain in 1843.	X
1921	First radio broadcast of a sporting event (Dempsey/Carpentier Heavyweight Championship Prize Fight, 2 July).	
1922	Ship-to-shore conversation by wire and wireless between Bell telephones in homes and offices and the S. S. America 400 miles at sea in the Atlantic.	Label 4
1922	Introduction of improved steel wall telephones and improved desk stands (Type 21).	
1922	Alexander Graham Bell dies at his summer home in Beinn Breagh, near Baddeck, Cape Breton Island, Nova Scotia (August 2). Telephone service is suspended for one minute (6:25pm-6:26pm) on the entire telephone system in the United States and Canada during the funeral service (4 August). British Broadcasting Corporation (BBC) is formed. (Royal Charter received in 1927).	
1923	7th June: Radio broadcasting networks had their beginning with a hook-up of four radio stations by long distance telephone lines.	X
1923	22nd December: Opening of second transcontinental telephone line via a southern route.	
1923	14050565 Bell telephone stations owned and connected. Successful demonstration of transoceanic radio telephony from a Bell telephone station in New York City to a group of scientists and journalists in New Southgate, England.	X
1923	First British Post Office announces adoption of Strowger system (with Director) for London.	

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Year	Event	Major event
1923	Meetings at New York and Chicago of the American Institute of Electrical Engineers (AIEE) are linked by long distance lines connected to loudspeakers so that both meetings could follow the same program (14 February).	
1924	AT&T offers Teletype system.	X
1924	Strowger exchange installed throughout Canal Zone. First Strowger Directors installed in Havana.	
1924	Directive short wave antenna is developed by Professor Hidetsugu Yagi and his assistant, Shintaro Uda.	
1925	Bell Telephone Laboratories founded. 1.5 million dial telephones in service out of 12 million phones in service.	X
1925	1st October: Opening of long distance telephone cable, New York to Chicago.	
1925	Introduction of the Monophone first hand set telephone of modern type.	
1925	The Combined Line and Recording (CLR) method of handling toll calls over long distances (100 miles or more) is introduced experimentally by Bell Systems. It reduces the handling of toll calls from 13 minutes (in 1920) to 7 minutes.	
1926	Inauguration of the direct stock ticker circuit from New York to San Francisco.	
1926	Baird in Scotland and Jenkins in the U.S. demonstrate TV using neon bulbs and mechanical scanning disks. P.M. Rainey at Western Electric patents the PCM methodology.	X
1926	Introduction of the Type 24 Dial modern, quiet-running, long-life calling device. Strowger system adopted by Japan.	
1926	7th March: First transatlantic telephone call, from London to New York.	Label 5
1927	7th January: Transatlantic telephone service inaugurated for commercial service via radiotelephony (3500 miles).	Label 5
1927	17th January: Opening of third transcontinental telephone line via a northern route.	
1927	7th April: World's first videophone call via an electro-mechanical AT&T unit, from Washington, D.C. to New York City, by then-Commerce Secretary Herbert Hoover.	
1927	First Director installation in London. Introduction of line switch with self-aligning plunger.	
1927	Philo Farnsworth demonstrates his all-electronic Television to potential investors by broadcasting the image of a dollar sign. Farnsworth receives backing and applies for a patent, but ongoing patent battles with RCA will prevent Farnsworth from earning his share of the million-dollar industry this invention will create.	
1927	First public demonstration of long distance transmission of television. Formal opening of telephone service between the US and Mexico, and also, Mexico to London, via New York.	X
1928	Zworykin files patents on electronic scanning TV using the iconoscope.	
1928	First extended use of Strowger 200-point Line finder. Introduction of improved Monophone designs.	

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Year	Event	Major event
1928	A joint meeting of the AIEE and the British IEE is held over radiotelephone channels, with the respective groups assembled in New York and London.	
1929	8th December: Opening of commercial ship-to-shore telephone service.	X
1929	Broadband coaxial cable invented by Lloyd Espenschied and Herman Affel.	X
1929	U.S. Navy begins use of Strowger equipment. Monophones made available in colour.	
1930	AT&T introduces much higher quality insulated wire.	
1930	3rd April: Opening of transoceanic telephone service to Argentina, Chile and Uruguay and subsequently to all other South American countries.	X
1930	Development of new small switchboards of unit type. Networks of small Strowger exchanges installed in Italy.	
1930	High-speed tickers can print 500 words per minute.	
1931	Development of Strowger Remote Toll Board. First installed in Elyria, Ohio.	
1931	Radio Astronomy - While trying to track down a source of electrical interference on telephone transmissions, Karl Guthe Jansky of Bell Telephone Laboratories discovers radio waves emanating from stars in outer space.	X
1931	AT&T inaugurates the Teletypewriter Exchange Service (TWX) November 21.	
1932	Development of unattended private automatic branch exchanges. Two-line Monophones introduced.	
1933	New small private automatic exchanges introduced.	
1933	Edwin Armstrong demonstrates frequency modulation (FM) to Sarnoff.	
1934	Congress passes Communications Act of 1934, with a goal of universal service at reasonable charges as its key tenet. Federal Communications Commission founded. Combined functions of RF spectrum allocation previously handled by the Federal Radio Commission and interstate regulation for common carriers. Introduced "value-of-service" pricing which required the subsidisation of residential subscribers to speed the availability of nationwide telephone service.	X
1934	Introduction of new self-contained desk Monophone moulded in Bakelite (Type 34A3).	
1935	25th April: First around-the-world telephone conversation by wire and radio. About 6700 telcos in operation.	Label 6
1935	New all positions transmitter. New Bakelite wall Monophone (Type 35A5).	
1935	Western Union's "Telefax" begins operating. Telefax sent telegrams, manuscripts, line drawings, maps and page proofs for magazines.	
1936	Small, compact community automatic exchanges introduced.	
1936	BBC begins regular television service.	X
1936	Invention of coaxial cable is announced at a joint meeting of the American Physical Society and the IRE (April 30).	X
1937	Bell introduces the Model 300 improved handset.	

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Year	Event	Major event
1937	The Western Electric type 302 telephone becomes available for service in the United States.	
1937	8th December: Opening of fourth transcontinental telephone line.	
1937	Seven-hour radio broadcast of the coronation of King George VI and Queen Elizabeth of England.	
1938	Bell introduces crossbar central office switches.	
1938	The power of radio is demonstrated by Orsen Wells with the broadcast of "War of the Worlds". This causes telephone traffic to peak in nearly all cities and on long distance lines.	X
1939	WU introduces coast-to-coast fax service. John Atanasoff and Clifford Berry invent the first electronic computer for calculating at the University of Iowa. In 1973 a judge ruled in a patent infringement suit that their research was the source of most of the ideas for the modern computer, but it was not programmable or Turing complete.	X
1939	The Golden Gate Exposition (San Francisco) and New York Worlds Fair are opened. These exhibit the newest technologies, including the Voder (synthesised speech) and television. FM is used by Bell Laboratories in a radio altimeter that uses signal reflections from the surface of the earth.	
1940	24th June: Television transmitted over coaxial cable from Convention Hall in Philadelphia to television studio in Radio City, New York.	
1940	FM Police Radio Communications begin in Hartford, CT.	
1941	Multi-frequency dialling introduced for operators in Baltimore, Maryland	
1941	First U.S. commercial coaxial cable installation, Minneapolis, Minnesota to Stevens Point, Wisconsin.	
1941	Konrad Zuse in Germany develops the first programmable calculator using binary numbers and boolean logic.	X
1941	The Japanese attack on Pearl Harbor affects the telephone system of the United States by causing tremendous traffic peaks in all cities, and an increase from 100 to 400 percent in long distance telephoning - which already is at a record high of 3 million messages. (The United States would again experience this phenomenon in 2001, during the 11 September attacks.) Radar successfully detects the attack on Pearl Harbor, but the warnings are ignored.	
1942	21st December: Opening of first all-cable transcontinental telephone line with completion of buried cable, connecting existing cable systems of East and West.	
1942	The first section of telephone line is completed along the Alcan Highway, from Edmonton, Alberta, to Dawson Creek, British Columbia. The Alcan Highway begins at Dawson Creek.	
1942	Telephone production is halted at Western Electric until 1945 for civilian distribution due to the retooling of factories for military equipment during WWII.	
1943	Philadelphia is the last city to have telephone service supplied by different local carriers (until later deregulatory moves by the U.S. Congress and the FCC). Western Union and Postal Telegraph permitted to merge.	

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Year	Event	Major event
1943	22nd August: First equipment for the dialling of called telephone numbers in distant cities directly by the operator placed in service in Philadelphia.	X
1943	Construction of a telephone line from Calcutta, India to Kunming, China, along Stilwell Road, begins at Ledo, Assam.	
1944	A telephone submarine cable is laid across the English Channel.	
1945	AT&T lays 2000 miles of coaxial cable.	
1945	Arthur C. Clarke proposes communications satellites.	X
1945	Western Union installs the first commercial radio beam system.	X
1945	Western Union and Postal Telegraph Company merge.	
1946	AT&T televises Army-Navy game in Philadelphia and transmits it to NYC	
1946	AT&T has 8 VF channels on microwave from Catalina Island to Los Angeles. Raytheon has a microwave link transmitting audio from WQXR in NYC to Boston.	
1946	FCC's Recording Devices Docket required telcos to furnish connecting arrangements for conversation recorders. The use of "beep tones" required when conversations are recorded.	
1946	12th February: New York to Washington co-axial cable circuits opened for television transmission on an experimental basis.	
1946	17th June: Opening of experimental mobile radiotelephone service in St. Louis.	Label 7
1946	Mobile telephone service is placed into commercial use in St. Louis, Missouri. The beam travelling-wave tube is announced by Bell Telephone Laboratories. This tube is an important amplifier for broadband communication.	Label 7
1946	National Numbering Plan (area codes)	
1947	Bell Telephone Laboratories has a 96-channel PCM experimental system working between Murray Hill, N.J. and NYC and quickly discovers the need for repeaters for long-distance service.	X
1947	15th August: Opening of commercial telephone service for passengers on certain trains running between New York and Washington, D.C.	Label 7
1947	13th November: Opening of New York-Boston radio relay system for experimental service. This is the first microwave relay system in the telephone network.	
1947	Invention of the germanium point contact transistor by Brattain and Bardeen at Bell Telephone Laboratories (December 23). The following year they develop the alloy junction germanium transistor.	Label 7
1947	December: W. Rae Young and Douglas H. Ring, Bell Labs engineers, proposed hexagonal cells for provisioning of mobile telephone service. Demonstration of mobile telephone equipment from a United Airlines plane to ground stations.	Label 7
1948	Phil Porter, a Bell Labs engineer, proposed that cell towers be at the corners of the hexagons rather than the centres and have directional antennas pointing in 3 directions.	

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Year	Event	Major event
1948	The Hush-A-Phone case begins. The Hush-A-Phone Corp. had developed and was marketing a cup-like device placed on a phone's mouthpiece to increase privacy of conversations. The Bell System complained to the FCC about this "foreign attachment".	
1948	Invention of the junction transistor.	X
1948	30th June: First public demonstration of the transistor by Bell Telephone Laboratories.	
1949	AT&T introduces the famous black rotary Model 500 telephone.	X
1949	Bell Labs publishes Shannon's seminal theory of relay logic that is critical in the development of modern computers.	X
1949	FCC's Jordaphone Docket (1949 - 1954). A precursor to Part 68. Jordaphone and three other manufacturers of answering machines sought FCC approval for their use on telco lines. The FCC decision left the matter to the states as only about 1% of telephone calls at that time were interstate. Commissioner Frieda Hennock filed her opposition in favour of the petitioners.	
1949	Justice Department files antitrust suit against AT&T. The Department wanted Bell to divest Western Electric, and to separate regulated monopoly services and unregulated equipment supply, among other actions.	X
1949	17th October: Dialling of transcontinental telephone calls by operators started with the joining of toll dialling networks on East and West coasts.	
1949	The volume of telephone calls reaches 180 million a day.	
1950	The Western Electric Type 500 telephone becomes available in the United States after announcement in 1949.	
1950	30th September: Television network facilities extended to include 72 television stations in 42 cities, making television available to one half of the United States' population.	
1951	10th November: Direct Distance Dialling (DDD) first offered on trial basis at Englewood, New Jersey, to 11 selected major cities across the United States; this service grew rapidly across major cities during the 1950s	
1952	The first database was implemented on RCA's Bizmac computer. Reynold Johnson, an IBM engineer, developed a massive hard disk consisting of fifty platters, each two feet wide, that rotated on a spindle at 1200 rpm with read/write heads. These were called "jukeboxes".	X
1953	John Pierce proposes deep space communication.	
1954	Gene Amdahl developed the first computer operating system for the IBM 704. Sony introduces the first transistor radio that sold for \$49.95. Raytheon introduces the transistor for hearing aids replacing its line of subminiature tubes. Zenith's highly successful hearing aids using subminiature tubes, about the size of a pack of cigarettes with a separate battery pack sold for about \$25.0. The new transistor hearing aids reduced the size of the electronic package to about the size of a box of matches with an internal battery and sold for about \$100. The first in-the-ear hearing aids appeared about 1955-1956.	

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Year	Event	Major event
1954	US Air Force's SAGE system sets precedent for computer communications, including use of modems.	X
1955	The laying of transatlantic cable TAT-1 began - 36 circuits, later increased to 48 by reducing the bandwidth from 4 kHz to 3 kHz	Label 8
1955	According to Ken Krechmer, A.W. Morten and H.E. Vaughan describe the development of a real modem in their BSTJ paper, "Transmission of Digital Information over Telephone Circuits", May 1955. Reynold Johnson at IBM develops the first disk drive.	
1955	Recorded announcements of disconnected and changed numbers begin to be used in some small dial offices.	
1956	AT&T's Consent Decree. In 1949, the Department of Justice wanted AT&T to divest itself of Western Electric. The court ignored the Department of Justice's request. Instead, as the result of the Consent Decree, AT&T got to keep WE; however, it could only stay in the field of telecommunications and it had to licence its patents to others.	X
1956	The Hush-A-Phone case was decided in favour of Hush-A-Phone Corp. It establishes that harmless non-Bell equipment may be attached to the network. Hush-a-Phone permitted the use of acoustically and/or inductively coupled answering machines, such as Jordaphone, and also fax machines. Previously, AT&T permitted only Government and newspaper wire services to connect fax machines and wire photo equipment.	X
1956	The Bell System and the British Post Office inaugurates service on the first transatlantic telephone cable, TAT-1, between Newfoundland and Scotland.	Label 8
1956	The 1956 Nobel Prize in Physics is awarded to the inventors of the transistor: Dr. Walter H. Brattain, Dr. John Bardeen and Dr. William Shockley.	X
1957	Soviet Union launches Sputnik, humanity's first artificial satellite, on 4th October.	X
1958	AT&T introduces datasets (modems) for direct connection. Jack Kilby, Texas Instruments, developed the first integrated circuit. TI introduces the silicon-based transistor which soon eclipsed germanium devices in production volume. Seymour Cray at Control Data Corporation develops the first transistorised computer, Model 1604. He later uses liquid nitrogen to enhance the speed of CDC's line of supercomputers.	X
1959	In the Above 890 ruling, the FCC makes available portions of the radio spectrum to private microwave systems. As a result, AT&T introduces the TH-1 1860-channel microwave system.	X
1960s	Bell Labs developed the electronics for cellular phones	X
1960	Bell Labs conducts extensive field trial of an electronic switching system at their central office in Morris, Illinois, known at the Morris System.	X
1960	There are now 3299 telephone companies.	X
1960	ECHO I communications satellite is launched on 12 August. Provides first satellite television broadcast of 1962.	X

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Year	Event	Major event
1960	Laser is invented.	X
1961	Initiation of Touch-Tone service trials	
1961	Bell Telephone Labs release design information for the touch-tone dial to Western Electric.	
1961	Len Kleinrock of MIT publishes “Information Flow in Large Communication Nets”, considered a seminal paper on packet-switching theory.	X
1962	Western Union offers Telex for international teleprinting.	
1962	AT&T introduces T-1 multiplex service (the first digital transmission system) in Skokie, IL. Telephone cables now start to use plastic insulation. Paul Baron of RAND introduces the idea of distributed packet-switching networks.	Label 9
1962	Comsat formed. American Broadcasting Company requests FCC to allow domestic satellites to distribute TV programs. Approximately 10000 computers are in service.	
1962	United States Congress passes the Communications Satellite Act. T1 carrier is put into commercial service. The first transatlantic transmission of a TV signal via the TELSTAR satellite (11th July). EES Electronic Switching Systems is introduced.	X
1963	Microwave Communications Inc. (MCI) filed an application with the FCC to offer specialised voice and data services over a microwave system it planned to build between Chicago and St. Louis.	
1963	AIEE and IRE merge to form IEEE (1st January). Paul Baran of RAND publishes “On Distributed Communications Networks”, outlining the operations of packet-switching networks capable of surviving node outages. NASA announces that the new Syncom II communications satellite has been used successfully to transmit voices live between the U.S. and Africa. At the time of the conversations, Syncom II hovers 22000 miles over Brazil. The satellite is the first successful synchronous satellite. This mean that the satellite’s revolution matches the daily revolution of the earth about its axis, so that the satellite seems to remain “stationary” over the same earth location. A telephone hotline connects Soviet and American leaders (30th August).	X
1963	BBN develops the first modem.	
1963	18th November: AT&T commences the first subscriber Touch-Tone service in the towns of Carnegie and Greensburg, Pennsylvania, using push-button telephones that replaced rotary dial instruments.	X
1964	IBM releases its famous Model 360 computer that eventually led to $100 billion in sales over its life cycle. George Heilmeier, at RCA’s research labs, invents the liquid crystal display. Douglas Englebart at SRI patented the idea of the mouse.	X

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Year	Event	Major event
1964	An improved stock ticker tape machine (designed, developed and manufactured by Teletype Corporation) is placed into service at the New York Stock Exchange. The ticker, which transmits stock prices to brokerage houses nearly twice as fast as the previous system, has a capacity of ten million shares a day without incurring delays (22nd June). IEEE Group on Communication Technology is formed (1st July)	
1965	31st May: AT&T introduces stored program controlled switching. The world's first electronic switching system commences commercial service in Succasunna, New Jersey in form of the 1ESS.	Label 10
1965	There are now 2421 telephone companies.	
1965	Charles Kao conceives of using light sent over glass fibres as a transmission medium. He works with G. A. Hackham and publishes an influential paper on fibre optics.	Label 10
1965	The first commercial communications satellite, Early Bird, later named Intelsat 1, is launched into orbit from Cape Kennedy and provides 240 circuits or one TV signal. The 85-pound satellite is a synchronous satellite, matching the earth's rotation to hover over the same spot all the time (6th April). The Soviet Union launches its first communications satellite and carried out transmissions of television programs. The satellite is named "Molniya 1", which translates to "Lightning 1" (23rd April).	Label 10
1966	Tom Carter sues AT&T to permit connection of his phone patch. Court remands the case to FCC (One writer stated Tom Carter filed for $1.25 million damages and received $300K. His original complaint had been filed in 1958).	
1966	Suggestions made by Kao and Hockham that optical fibre could be used for long distance transmission.	Label 10
1966	Lawrence G. Roberts of MIT publishes "Towards a Cooperative Network of Time-Shared Computers" which outlines the ARPANET plan. Worldwide direct telephone dialling has its first public demonstration, a call from Philadelphia to Geneva, Switzerland (15th June).	X
1967	Bell Laboratories announces a new solid-state source of high frequency radio waves. The "LSA diodes" emitted millimetre waves, a part of the radio frequency range that could carry about nine times more telephone calls than all lower frequencies combined. An LSA diode and its power supply is about as large as a deck of cards (15th February). An experimental cordless extension telephone is introduced by Bell Laboratories (30th June).	X
1968	FCC approves Carterphone Decision. AT&T ordered to revise tariffs effective 1/1/69 to permit connection of CPE. (It took about 10 years of legal action to get Part 68 of the FCC rules in place and operational by 1978). AT&T starts development of the Integrated Digital Services Network (ISDN). Gary Englehart at Stanford Research Institute demonstrates the first combination of a keyboard, keypad, mouse, windows and word processor. Dan Noble, IBM, developed the 8-inch floppy disk. Its capacity increased from 33K in 1971 to 1200K in 1977. AT&T starts 56 Kbps service. Pieter Kramer (Philips) invents the compact disk.	X

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Year	Event	Major event
1968	FCC's Carterfone decision permits interconnections of non-Bell equipment to telephone lines.	
1968	FCC starts proceeding to set aside spectrum for land mobile communications.	Label 10
1968	Bell System adopts the use of "911" as a nationwide emergency telephone number (12th January). Huntington, Indiana became the first U.S. city served by the Bell System to receive the new universal emergency telephone number "911" (1st March).	
1969	FCC asks National Academy of Science to recommend an interconnection policy. The Department of Defense initiates the ARPANet, which led to the development of Internet. Initially computers at Stanford University and UCLA are connected.	X
1969	In its MCI decision, the commission authorises MCI to build and operate private line facilities between St. Louis and Chicago.	
1969	ARPANET begins 4-node operation (UCLA, Stanford Research Institute (SRI), UC Santa Barbara and University of Utah)	
1969	Video and Audio are transmitted back from the first Moon landing (20th July). UNIX Operating System is developed.	X
1970	AT&T introduces its ESS#2 electronic switch. Intel introduces its popular 4004 4-bit microprocessor which starts the evolution of Intel's famous line of 386, 486 and Pentium processors. There are now 1841 telephone companies. AT&T permitted to sell its teletype (TWX) service to Western Union. FCC approves the Domestic Satellite Order (which was nine years in the making).	
1970	Amos E. Joel, Jr. of Bell Labs invented the "call handoff" system for "cellular mobile communication system" (patent granted 1972).	X
1970	Bell Telephone Labs release design information to Western Electric for the production of Modular Telephone Cords and Jacks.	
1970	Corning Glass demonstrate highly transparent fibres, and Bell Laboratories demonstrates semiconductor lasers that could operate at room temperature; these demonstrations help establish the feasibility of fibre-optic communications.	X
1971	AT&T submitted a proposal for cellular phone service to the U.S. Federal Communications Commission (FCC).	X

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Year	Event	Major event
1971	The NAS Report recommended that an equipment certification program could be established to prevent harm to the network caused by hazardous voltages, excessive signal power, improper network control signalling and line imbalance. FCC establishes the PBX and Dialer and Answering Devices Committees to recommend certification standards based on the NAS Report. Satellite decision nine (Western Union wanted to make use of excess CO computer capacity to do data processing. This decision led to procedures to assure no cross-subsidisation between regulated and unregulated activities). Gary Starkweather, Xerox, patents first laser printer. A couple of years later HP and Canon jointly introduce the first commercial laser printers. FCC establishes the PBX Advisory Committee and the Dialer and Answering Devices Committee and were terminated on the approval of Part 68. The PBX Committee's report was turned over to EIA where it eventually as a voluntary standard, 470. The Dialer and Answering Devices meetings were so contentious that no report was published. The Specialised Common Carrier Decision allowed MCI to get its private line service started over its St. Louis - Chicago route.	
1971	The Intelsat IV communications satellite goes into commercial operation. Initially it has 830 circuits in service and linked ground stations in 15 countries. The DUV (Data Under Voice) is introduced. It permits signals to "hitch-hike" on existing microwave radio systems by using the lower end of the frequency band not normally used for voice. Ray Tomlinson writes the first email program. The @ sign is used for the first time in an email address.	X
1972	IEEE Communications Society is established on 1 January. Jon Postel writes the specifications for Telnet. IEEE Proceedings publishes its first issue on computer communications. Guest Editors are Paul Green and Robert Lucky. A demonstration of the ARPANET at the 1972 IEEE International Conference on Computer Communications.	

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Year	Event	Major event
1973	Docket 19419 on Pricing of Datasets opened up the necessary technical background for Docket 19528 which led to the development of Part 68. This docket also established a Federal-State Joint Board. A two-week cross-examination of Larry Hohmann, AT&T's Director of Engineering by FCC attorney Michael Slomin provides much of the technical information that led to Part 68 of the FCC's Rules. The Joint Board's recommendations were adopted in part. A companion docket covered standardisation of physical connectors needed for the interconnection program proceeded in parallel. In Docket 19808, the Telerent Decision, the Commission permitted states to have their own interconnection programs so long as they were no more stringent than the Federal program. This decision was appealed twice to the 4th Circuit Court then went all the way to the Supreme Court for final approval. As a result telcos when they want to initiate a special intrastate service must file a tariff for the service and a "network disclosure" document that clearly identifies service and equipment requirements. Docket 20003 was an economic study prepared by the Commission for Congress to show estimated economic effects of permitting private ownership of telephone terminal equipment an permitting competition in interstate telecommunications.	
1973	Bell Telephone Labs released design information to Western Electric for production of the Com-Key 416, the first KTU-less key system which was less susceptible to damage caused by lightning storms.	
1973	Robert Metcalfe invents Ethernet at Xerox PARC. Ethernet uses a cable rather than a radio channel as the transmission medium. The "Touch-a-matic" telephone is introduced. It can automatically dial a call anywhere in the U.S. at the touch of a single button. Its solid-state memory allows dialling up to 32 pre-coded telephone numbers. Construction of a new, high-capacity coaxial cable system, called L5, is completed between Pittsburgh and St. Louis. It has the capacity of carrying 108000 simultaneous telephone conversations, three times the capacity of any previous system. File Transfer Protocol (FTP) is introduced.	X
1973	Packet switched voice connections over ARPANET with Network Voice Protocol (NVP).	X
1973	3rd April: Motorola employee Martin Cooper placed the first hand-held cell phone call to Joel Engel, head of research at AT&T's Bell Labs, while talking on the first Motorola DynaTAC prototype.	Label 11
1974	First domestic satellites in operation. Western Union places Westar satellite in operation. AT&T introduces the digital subscriber loop. BBN opens the first public packet-switched network. The Department of Justice files its antitrust suit against AT&T. The Consent Decree, resulting therefrom, required AT&T to divest itself of the 24 Bell Operating Companies by 1984. Value-added (packet-switched networks) come on the scene.	X

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Year	Event	Major event
1974	Vinton Cerf and Robert Kahn publish "A Protocol for Packet Network Interconnection", in IEEE Communications Magazine, which outlines design of a Transmission Control Program (TCP). This discusses connecting networks together to form an "internet". Western Union launches Westar, the nation's first domestic communications satellite. New York Telephone inaugurated Dial-A-Joke, an addition to the recorded announcement field. During the first month of operation, more than 100000 calls a day are made to the number.	X
1975	Summary of 1975: There are now 1618 telcos and 140 million phones in the U.S. Bell companies supply 85% of the lines; GTE: 10%. Smallest telco had 19 subscribers.	
1975	Bell Telephone Laboratories released production design information to Western Electric for electronic key systems.	
1975	The First Report and Order in Docket 19528 led to Part 68 of FCC rules. A court stay was lifted on June 16, 1976 to permit the registration program to go into effect for toll restrictors, answering machines and data modems. Popular Electronics features the MITS Altair 8800 computer which is considered the first personal computer. Fibre optics being trialled in the U.S. and Europe. FCC's Docket 20099 meetings from 1974 through 1983 establishes carrier-to-carrier interconnection standards. After the breakup of the Bell System, this activity was taken over by the Exchange Carriers Standards Association, later known as the Alliance for Telecommunications Industry Solutions (ATIS). Docket 20774 establishes standard plugs and jacks for the registration program.	X
1975	Bolt, Beranek and Newman (BBN) opens Telenet, the first public packet data service. Viking is launched. Lands on Mars in 1976 and sends back data to Earth. Transmission testing begins on the T4M, highest-capacity, short-haul digital transmission system in the U.S. The new system, linking Newark, NJ to New York City, transmits 274 million "bits" of information per second over a single coaxial tube.	X
1976	Kazuo Hashimoto invents Caller ID	X
1976	Digital radio and time division switching introduced. Alan Shugart, IBM, introduced the 5.25-in floppy in 1976. (Much later, in 1987, SONY introduced the 3.5" floppy). Floppies were first introduced with IBM's PCs when they first came on the market in 1981. The telephone companies support "The Consumers Communications Reform Act of 1976" H.R. 12323, which was endorsed by more than 90 members of the House. This proposed legislation would have retained the telephone companies' monopoly. The FCC counters with its Docket 20003, Economic Implications and Interrelationships Arising from Policies and Practices Relating to Cusotmer Interconnection, Jurisdictional Separations and Rate Structures. Resale and sharing of carrier services permitted. Other Common Carriers (OCCs) now have access to telco Foreign Exchange (FX) and Common Control Switching Arrangement (CCSA) private network facilities.	

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Year	Event	Major event
1976	Centennial of the Telephone. IEEE establishes the Alexander Graham Bell Medal to commemorate the centennial of the telephone's invention and to provide recognition for outstanding contributions in telecommunications. Amos Joel, William Keister and Raymond Ketchledge are the first recipients. COMSTAR is launched and begins commercial service. It is in permanent orbit over the Galapagos Islands.	
1977	The Second Report and Order in Docket 19528 survived challenge in the Court of Appeals 4th Circuit. This item provided rules for telephones, key systems and PBXs. The order was challenged again all the way to the Supreme Court, which permitted the registration program to begin on October 17, 1977. The FCC completed program implementation rules by July 1, 1978 in the Third Report and Order. Registration of phones, KTSs and PBXs begin. MCI wins a court challenge to its Execunet Service which permitted the public to make use of its long distance facilities.	
1977	Voyager spacecraft is launched. Sends back signals from Jupiter (1979-1980), Saturn (1981), Uranus (1986) and Neptune (1989). Bell Laboratories announces the development of the MAC-8, a microprocessor suited for a wide range of telecommunications applications.	X
1978	Bell Labs launched a trial of the first commercial cellular network in Chicago using Advanced Mobile Phone System (AMPS).	Label 12
1978	World's first NMT phone call in Tampere, Finland.	X
1978	Commission rejects telephone companies' request for the Primary Instrument Concept in which all subscribers would be required to have at least one phone provided by the telephone company.	
1978	TAT-1, the world's first transoceanic telephone cable was retired (27th November). TCP split into TCP and IP.	X
1979	The Fourth Report and Order established rules regarding equipment-to-equipment connections. Docket 79-143 established rules for analog OPS and tie line equipment. GTE requests FCC to convene a special task group to develop recommendations for inclusion of T-1 services into Part 68. Dan Brinklin, while still in college, introduces the Visicalc spreadsheet which becomes a spectacular success. Docket 79-105 requires telcos to stop capitalising premises wiring and the states set up amortisation schedules for the eventual transfer of premises wiring ownership to the premises owners.	
1979	A 62000-mile microwave telecommunications system is completed within Saudi Arabia.	
1979	VoIP - NVP running on top of early versions of IP	

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Year	Event	Major event
1980	AT&T introduces the DataSpeed 40, a forerunner of the current generation "smart terminals" having the capability of doing various forms of data processing rather than serving solely as input terminal to a computer. This led to the Computer II Decision which came up with a binary test: Was the device for "basic" service; or was it for "enhanced" service? Enhanced services had three subdivisions: Protocol conversion, data processing, and information retrieval. All of this led to the Computer III Decision and the Open Network Architecture concept in 1989. Digital local offices and optical fibre transmission being deployed. Switching System #7 is being gradually deployed.	
1980	First use of the "900" number.	
1981	BT introduces the British Telephone Sockets system.	
1981	Docket 81-216, the "Omnibus Docket" was so called because it contained about two dozen items, including make-busy, digital systems, more on premises wiring, party lines, reducing dc on-hook resistance requirements and many more. It took several years to clear all of these items. Hayes introduces its landmark 300-bps modem. IBM introduces its PC in August 1981.	
1981	Bell Telephone Labs design of a network-embedded database of Personal Identification Numbers (PINs) for calling card customers to be accessed by public telephones over Signaling System 7. (Today, improved architectures of this kind underlie all Intelligent Network services.)	
1981	The world's first fully automatic mobile phone system NMT is started in Sweden and Norway. This is soon followed by Saudi Arabia.	
1981	A new telephone service, DIAL-IT allowed a caller to listen to the voice communications between the Space Shuttle Columbia and the ground command center.	X
1982	8th January: Antitrust suit dropped after AT&T accepts government's proposal.	X
1982	First long-distance, fibre-optic transmission system is installed between New York and Washington, D.C.	Label 13
1982	The first full-colour two-way video teleconferencing service is offered. The development of TFM (Time Frequency Multiplexing).	
1982	FCC approved AT&T proposal for AMPS and allocated frequencies in the 824-894 MHz band.	X
1983	Last manual telephone switchboard in Maine is retired	
1983	In the CBEMA Decision, an outgrowth of the Computer II Decision, the Commission requires telcos to publish a "Network Disclosure" statement providing information of interconnection and operability requirements for new services. Carolyn Doughty, Bell Telephone Laboratories, files a patent on Caller ID.	

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Year	Event	Major event
1983	The Cleaved Coupled-Cavity (C3) laser was introduced. The single frequency tunable laser emitted a light so pure that over a billion bits of information per second could be sent through a glass fibre (April). The first U.S. commercial cellular phone system is introduced in Chicago (13th October).	
1984	Breakup of AT&T (1st January): Court orders divestiture of AT&T based on Department of Justice suit. Fred Henck, publisher of Telecommunications Reports and Bernie Strassburg, retired Chief of the Common Carrier Bureau, in their book covering the divestiture of AT&T estimated that legal fees and settlements cost AT&T more than $5 billion. (A Slippery Slope - The Long Road to the Breakup of AT&T). Another book on this subject is "The Rape of Ma Bell".	X
1984	FCC decisions released relative to turning over previously installed premises wiring to premises owners; Congressionally mandated hearing aid-compatibility requirements for "essential" phones. FCC permits registration of privately owned "instrument operated" coin phones.	
1984	IEEE Centennial. Local area signalling service is introduced. The service is used to trace nuisance calls, transfer calls, and provide other advanced calling services (20th May). AT&T and NASA space shuttle Discovery launch its second Telstar 3 satellite. 1st September: Domain Name Service (DNS) is introduced. DNS is used mostly to translate between domain names and IP addresses, and to control Internet email delivery.	X
1984	AT&T completes the divestiture of its local operating companies. This forms a new AT&T (long distance service and equipment sales) and the Baby Bells.	
1985	FCC decisions related to registration of CPE for T-1 and subrate digital services	
1985	AT&T Bell Laboratories combine 10 laser beams on a single optical fibre demonstrating the capability of lightwave systems to carry 20 billion bits per second (equal to 300000 telephone calls.) Symbolics.com is assigned on 15th March to become the first registered domain.	X
1986	FCC decision to phase out line-powered channel service units. The National Science Foundation introduces its 56kbps backbone network.	
1986	TAT-3 transatlantic cable is retired (1st September) An Integrated Services Digital Network (ISDN) is deployed, capable of handling voice, data and video (16th December).	
1987	Ameritech files for registration of switched 56 Kbps digital service CPE. This was integrated with the SW Bell petition to include ISDN in the rules in October of 1991 (It took until 1991 for EIA to develop technical standards for this service). SONY introduces the 3.5-in floppy. Philip Estridge, IBM, developed the first hard drive for PCs. It held 10MB. N.J. Bell is the first to implement Caller ID.	
1987	Superconductivity is discovered - the transmission of electricity without resistance through low temperature material.	X

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Table A7 – continued from previous page

Year	Event	Major event
1987	TDD (telecommunications device for the deaf) is initiated.	
1987	Bellcore introduces the Asymmetric Digital Subscriber Line (ADSL) concept which has the potential of multimedia transmission over communication network's copper loops.	
1988	Western Union Telegraph Company reorganised as Western Union Corporation. The telecommunications assets were divested and Western Union focuses on money transfers and loan services.	X
1988	U.S. Congress passes the Telecom Trade Act of 1988 in response to alleged dumping of telecom systems in the U.S. by foreign manufacturers. One aspect was the requirement of all imported telecom equipment to comply with all applicable FCC requirements. Enforcement is by U.S. Customs.	
1988	FCC issues Docket 88-57, based on an EIA petition for clarification of previous premises wiring policies (An order was released in 1990 which elicited about ten petitions for reconsideration. The final order was released in June 1997 clearing many outstanding issues).	
1988	First transatlantic fibre-optic cable, TAT-8, opens between New Jersey, England and France, carrying 40000 circuits.	Label 14
1989	Congressional decision requiring all new customer-owned phones to be hearing aid compatible. The Computer III Decision leading to the Open Network Architecture concept was to allow unbundled access to all enhanced service providers, everyone receives equal quality and pricing, standard accounting guidelines and to have the BOCs determine what services are needed and how to tariff these services (There were 118 different services proposed; about half of them could be offered and about 20% of the proposed would have to wait for new technology). NSF increases its backbone network from 56kbps to T-1.	
1990	Analog AMPS was superseded by Digital AMPS.	
1990	AT&T filed a petition to strengthen DID rules for prevention of toll fraud. EIA filed a petition to require digital security coding for cordless phones to prevent random dialling that interfered with 911 operations. Docket 90-313 requiring hotels/motels and coin phones to provide equal access to competing long distance carriers was resolved in 1992.	
1991	Docket 91-281 establishing nationwide caller ID went into effect in late 1995. There are a number of related issues yet to be resolved. The Telephone Consumers Protection Act, among other things, required the use of "fax branding" to identify the source of incoming faxes. There were a couple of court cases which delayed application of fax branding to PC fax cards until 1995. Southwestern Bell files to include ISDN in Part 68. The final rules for ISDN went into effect on 13th November, 1996 (Canada had essentially the same rules in place for the preceding five years). Note that AT&T started development of ISDN about the same time that Part 68 was introduced.	
1991	The GSM mobile phone network is started in Finland, with the first phone call in Tampere.	

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Table A7 – continued from previous page

Year	Event	Major event
1991	The World Wide Web is born - the brain child of CERN physicist Tim Berners-Lee. Congress required all agencies to metricise their rules. A major impact was on Part 68 plug and jack drawings. The first audio and video multicasts are broadcast over the Internet.	X
1993	Telecom Relay Service (TRS) available for the disabled. The NSF network backbone jumps from T-1 to T-3. The Internet browser MOSAIC is introduced at the University of Illinois.	
1994	TRS becomes the fastest growing telecom service in the U.S. The Commission requested comments on technology for location of any station behind a PBX that made an E911 call. There were over 120 responses. The Netscape Internet browser is introduced. Canada, Mexico, and the U.S. sign the NAFTA agreement. NSF is working to build a very high-speed backbone called VBNS. Internet is pretty much world-wide with the exception of most of the African interior, Pakistan, Mongolia, Cuba and some areas in South America and South-east Asia. Real Audio introduced to Internet which allows one to hear in near real time. Radio HK, the first 24-hr Internet only radio station, starts broadcasting.	X
1994	The IBM Simon becomes the first smartphone on the market.	Label 15
1995	There are more than 33.8 million wireless subscribers, representing approximately 13% of the total U.S. population.	Label 15
1995	Caller ID implemented nationally in USA	
1996	TIA files to harmonise Part 68 with Canada's CS-03 after working five years with Canada's TAPAC group, and successfully achieves industry concurrence before filing. Canada approved its version on 14th August, 1996. Because of the impact of Congress' revision of the Telecommunications Act, the FCC was swamped with 80 new rulemakings to be completed by August of 1996, and so approval of the harmonised Part 68/CS-03 was delayed. It was approved on 30th July, 1997. The Commission instituted a "negotiated rulemaking" procedure for requiring phones in the workplace to be hearing aid compatible. As a result, approval took slightly more than a year and was announced in the Federal Register on 14th August, 1996. It was subsequently announced that the industry will form a new group (Lockheed) to administer the new North American numbering plan. A waiver process was adopted that allows manufacturers to register stutter dial-tone devices. Currently, there are almost 1400 telcos still in business. In 1996, Digital Equipment Corporation introduced its line of Alpha microprocessors using 64-bit RISC architecture and operating up to 533 Mbps.	
1996	February: U.S. Congress passes the 1996 Telecommunications Act which requires FCC to develop 80 new rulemakings within a six-month period leading to increased competition is all aspects of telecommunications. "Central-office implemented coin phones" are now required to be registered as a result of opening this market to competition.	

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Table A7 – continued from previous page

Year	Event	Major event
Early 1996	In early 1996 ANSI approved an ADSL standard for the Discrete Multitone (DMT) version. Another competing concept called Carrierless Amplitude and Phase Modulation (CAP) was developed. The ADSL concept spawned an explosion of related concepts that permit transmission over copper up to close to 100Mbps. New copper fabrication techniques opened the avenue of very high speed data (multimedia) transmission in excess of 100 Mbps over useful ranges for premises wiring.	
1996	September: Rockwell announced a 56 kbps modem chip set designed for Internet applications. 56K download (PCM); 33.6 upload (analog). Technical committees start development of standards for this new technology. Controversy erupts over the fact the modulation technology limits the theoretical speed to about 53K because of Part 68's signal power limitation requirements to prevent crosstalk to third parties. In reality, because of line impairments the fastest practical speed is around 42 to 44K.	
1996	November: FCC network protection standards for Switched 56 and ISDN go into effect. USTA Annual Report says there are 170 million copper access loops in service nationwide, increasing at the rate of 5 million annually. Internet 2 is proposed to connect university computers together by means of one gigabyte pipes using SONET and ATM networks.	
1997	25th February: Lucent announced development of wireless loops with 128K ISDN capability. Rockwell receives FCC registration for its 56K PCM modem to be used by Internet service providers.	
1997	12th June: The U.S and the E.U. reach agreement on mutual recognition of product testing and approval requirements covering everything from lawnmowers, pharmaceuticals, recreational craft to telecom equipment.	
1997	17th June: FCC issues NPRM for BICSI petition to require the use of twisted-pair premises wiring to prevent crosstalk. Many issues outstanding from the premises wiring docket 88-57 finally resolved. Microsoft buys WebTV that claims to have 85000 subscribers. Canada releases draft of its proposed ADSL terminal equipment standards covering DMT and CAP/QAM technologies.	
1997	30th July: FCC approves the harmonisation of Part 68 and Canada's CS-03 network protection standards to be effective 20th April, 1998.	
1998	January: Rockwell, Nortel, Paradyne and others announce an ADSL-lite program called Consumer ADSL or CDSL which will download at about 1Mbps based on CAP technology. In contrast the T1E1 and international standards seem to be heading for DMT technology with download speeds around 6 to 8 Mbps. Other competing modes include Rate Adaptive DSL and another called Multiple Virtual Line (MVL) which can offer up to eight virtual phone lines sharing 768 kbps in one or both directions up to 24 kilofeet and working over in-home wiring.	

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Table A7 – continued from previous page

Year	Event	Major event
1998	February: V.90 56K standard was approved ending months of difficult negotiations and modem wars. Most of the older 56K modems can be upgraded by software downloading to work with the new standard.	
1999	Creation of the Asterisk Private branch exchange	
2002	11th June: Antonio Meucci is recognised for "...his work in the invention of the telephone" (but not "...for inventing the telephone") by the United States House of Representatives, in United States HRes. 269.	
2002	21st June: The Parliament of Canada responds by passing a motion unanimously 10 days later recognising Alexander Graham Bell as the inventor of the telephone.	
2005	Mink, Louisiana finally receives traditional landline telephone service (one of the last in the United States).	X

Table A8: Timeline of lighting [Waide et al., 2006, Hanna et al., 2015, Almeida et al., 2014, Sandahl et al., 2006, Tao, 2012, Baldwin and Mace, 2016]

Year	Event	Major event
125000 BC	Widespread control of fire by early humans	
70000 BC	A hollow rock, shell, or other natural found object was filled with moss or a similar material that was soaked in animal fat and ignited	
c. 3000 BC	Candles are invented. Some time later, oil lamps are developed	
1780	Aimé Argand invents central draught fixed oil lamp	X
1784	Argand adds glass chimney to central draught lamp	
1792	William Murdoch begins experimenting with gas lighting and lights his house and office by means of gas	X
1800	French watchmaker Bernard Guillaume Carcel overcomes the disadvantages of the Argand-type lamps with his clockwork fed Carcel lamp	X
1800-03	Humphry Davy remarks first carbon arc when using Voltaic piles (battery) for his electrolysis experiments	X
1802	Humphry Davy demonstrates arc lighting	X
1802	William Murdoch illuminated the exterior of the Soho Foundry with gas	
1805	Philips and Lee's Cotton Mill, Manchester was the first industrial factory to be fully lit by gas	
1809	Humphry Davy publicly demonstrates first electric lamp over 10000 lumens, at the Royal Society	X
1813	National Heat and Light Company formed by Fredrich Winzer (Winsor)	
1815	Humphry Davy invents the miners' safety lamp	
1835	James Bowman Lindsay demonstrates a light-bulb-based electric-lighting system to the citizens of Dundee, Scotland	X
1840	First paraffin (kerosene) lamps	X
1841	Arc lighting used as experimental public lighting in Paris, France	
1853	Ignacy Lukasiewicz invents the petroleum lamp	X
1854	Heinrich Göbel invents the first true light-bulb, using a carbonised bamboo filament	X
1856	Glassblower Heinrich Geissler confines the electric arc in a Geissler tube	
1867	A.E. Becquerel demonstrates the first fluorescent lamp	X
1874	Alexander Lodygin patents an incandescent light bulb	X
1875	Henry Woodward patents the electric light-bulb	X
1876	Paul Jablochkoff invents the Jablochkoff candle, the first practical carbon arc lamp, for public street lighting in Paris	

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Table A8 – continued from previous page

Year	Event	Major event
1878-79	Thomas Edison and Joseph Wilson Swan both patent the carbon-thread incandescent lamp, which lasts for approximately 40 hours. Swan successfully sues Edison but eventually sells his patent rights to him	Label ICD1
1880	Edison produces a 16-watt light bulb that lasts 1500 hours	Label ICD1
1882	Introduction of large scale direct current based indoor incandescent lighting and lighting utility with Edison's first Pearl Street Station	Label ICD1
1885	Incandescent mantle invented, revolutionising gas lighting	X
1886	Great Barrington, Massachusetts demonstration project, a much more versatile (long distance transmission) transformer based alternating current based indoor incandescent lighting system introduced by William Stanley, Jr. working for George Westinghouse. Stanley lit 23 businesses along a 4000 feet length of main street stepping a 500 AC volt current at the street down to 100 volts to power incandescent lamps at each location	X
1893	Nikola Tesla uses cordless low-pressure gas-discharge lamps, powered by a high-frequency electric field, to light his laboratory	
1893	GE introduces first commercial fully enclosed carbon arc lamp. Sealed in glass globes, it lasts 100h and therefore 10 times longer than previous carbon arc lamps	Label ICD2
1893	Nikola Tesla puts forward his ideas on high frequency and wireless electric lighting which included public demonstrations where he lit a Geissler tube wirelessly	Label ICD2
1894	D. McFarlane Moore creates the Moore tube, precursor of electric gas-discharge lamps	
1897	Walther Nernst invents and patents his incandescent lamp, based on solid state electrolytes	Label ICD2
1903	Peter Cooper Hewitt demonstrates the mercury vapour lamp, i.e. a fluorescent lamp	X
1910	William Coolidge invents a way to make a tungsten filament that outlasts all other types of filament (i.e. the Tungsten light bulb is invented)	Labels H1 & ICD3
1910	Georges Claude demonstrates neon lighting at the Paris Motor Show	X
1911	Georges Claude develops the neon lamp	
1925	The first internal frosted light bulbs were produced	Labels ICD4 & LFT1
1926	Edmund Germer patents the fluorescent lamp	Label LFT1
1932	The first low-pressure sodium lamp is developed by Philips and used mainly for street lighting	
1933	First Fluorescent tubes installed	Labels CFL1 & LFT2
1937	Linear Fluorescent Lamps/Lights (LFLs) are first commercialised	Labels CFL1 & H2 & LFT3

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Table A8 – continued from previous page

Year	Event	Major event
1939	Fluorescents made available for wider sale	Labels CFL1 & H2 & LFT3
1948	Halophosphor LFLs pioneered	Label LFT4
1959	The first tungsten halogen lamp is developed	Labels H3 & ICD5
1962	Nick Holonyak Jr develops the first practical visible-spectrum LED	Label LED1
1965	Metal halide HID lamps are commercialised	
1970	Commercialisation of high-pressure sodium vapour HID lamps	
1972	John Campbell patents first practical CFL	Labels CFL2 & LFT5
1976	Compact Fluorescent "Spiral Lamp" design developed by Edward Hammer but GE deems it too fragile to make with existing manufacturing technology	
1976	Hollister introduces magnetic-fluorescent lamp (but not manufactured)	Label LFT6
1976	Jan Hasker (Philips) develops the 'Recombinant Structure CFL'	
1978	T8 LFLs are commercialised	Label LFT6
1979	Phillips unveils first electronic ballast CFL	Label CFL3
1980	CFLs are commercialised	Label CFL3
1980	Tungsten halogen lamps are commercialised	Labels H4 & ICD6
1981	Thorn Lighting exhibits the world's first ceramic metal halide lamp at the Hanover World Light Fair	X
1981	Philips sells their first Compact Fluorescent Energy Saving Lamps, with integrated conventional ballast	Label CFL3
1982	Phillips starts using new rare earth phosphors that emit warmer colour of light and increase light output	Label LFT7
1985	GE produces first competing product	
1985	Osram enters the CFL market with the first electronic Energy Saving Lamps to be very successful	
1986	The "White" SON sodium vapour lamp is introduced	
Late 80s	Utilities start offering CFL bulbs to customers	X
1990	22nd April: Earth Day turning point in U.S. consciousness about energy efficiency, climate change, ozone depletion. Three books (50 Simple Things You Can Do to Save the Earth, Consumer Guide to Home Energy Savings, and The Green Consumer) sell millions of copies, and recommend the use of CFLs	Label CFL4
1990	Worldwide sales of CFLs = 83 million	
c. 1990	"High Brightness" Red, Orange, Yellow, & Green LEDs developed	Label LED2

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Table A8 – continued from previous page

Year	Event	Major event
1991	CFLs have 1% of US bulb sales volume, 2% of world bulb sales	
1991	Philips invents a fluorescent light bulb that lasts 60000 hours. The bulb uses magnetic induction	Labels CFL4 & LFT8
1992	Induction lamps are commercialised	
1992	In 1992, a visible blue and green InGaN LED was developed by Nichia, attaining 10% efficiency. The InGaN LED was a key milestone leading to white LED lighting	Label LED3
1992-94	A team at Nela Park, Cleveland, GE, with Jack Strok, creates ceramic metal halide lamps (CMH). Philips follows under W.de Kock and calls their versions CDM Ceramic Discharge Metal. Sales begin 1994. This technology improves to be a superior lighting technology with up to 150 lm/W with good colour rendering and 20000 hours life, whilst maintaining very high lumen rating	
1994	T5 lamps with cool tips are introduced to become the leading fluorescent lamps with up to 117 lm/W with good colour rendering. These and almost all new fluorescent lamps are to be operated on electronic ballasts only	Label LFT9
1994	First commercial sulphur lamp	X
1995	Spiral lamps appear on the market	X
1995	T5 LFLs are commercialised	Label LFT9
1995	Shuji Nakamura at Nichia labs invents first blue and, with additional Phosphor, white LED, and starts an LED boom	Label LED4
1995	"High Brightness" Blue & Green LEDs	Label LED4
1996	First white LED introduced by Nichia	Label LED4
1997	Philips and TCP introduce dimmable screw-based CFLs	X
1997	Worldwide sales of CFLs = 356 million	
1997	ENERGY STAR Residential Light Fixtures Program started in the United States. This brought a benchmark of lighting performance and quality as well as a clearly recognisable U.S. brand to the marketplace	X
1998	ENERGY STAR torchieres hit the market and sell a million units by September 1999	
1998	U.S. DOE's Sub-compact CFL Technology Procurement program started, administered by PNNL	X
1999	The U.S. DOE ENERGY STAR screw base CFL program is launched. This continued to help the utilities and regional market transformation groups to rally their marketing strategies	
2000	Beginning of U.S. West Coast Energy Crisis	Labels CFL5 & H5 & ICD7 & LED5 & LFT10

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Year	Event	Major event
2000	Program for Evaluation and Analysis of Residential Lighting (PEARL) started in 2000 as a watchdog organisation in response to complaints received by utility managers about the quality of ENERGY STAR rated products	
2000	White LED light demonstrates incandescent efficacy (17 lm/W)	Label LED5
2001	U.S. DOE launches R-CFL Technology Procurement Project to encourage the development of reflector style CFLs that perform well in high heat applications, such as recessed can fixtures	
2001	EU imposes an anti-dumping duty of 66.1 % on CFL-I bulbs, so China turns to U.S. resulting in glut of low-cost CFLs on US market (EU Regulation 1470/2001)	
2001	Rolling blackouts in California prompt massive regional CFL promotions and giveaways	Label CFL5
2001	Drought in U.S. Northwest prompts regional CFLs programs due to hydro power shortages	
2001	'Change a Light, Change the World' campaign launched with nationwide radio, tv and print advertising of ENERGY STAR CFLs in the U.S.	X
2001	New ENERGY STAR requirements including third-party testing and interim life testing	
2001	U.S. CFL sales surge to fourth quarter highs of 2.1% of U.S. lamp market, to 8.5% in California and to 12% in Northwest	
2002	CFL prices are down from $20+ per bulb in 1990 to $9 for a 4-pack without utility subsidy in mass merchandise stores like K-mart, WalMart and Costco around the U.S.	
2003	U.S. DOE, American Lighting Association, and Consortium for Energy Efficiency start CFL lighting fixture design competition called "Lighting for Tomorrow"	
2005	EU extends the anti-dumping duty from 2001 to include shipments from Philippines, Pakistan, and Vietnam. This was as a result of some Chinese companies affected by the 2001 action that had been shipping "kits" of partially manufactured CFLs to these countries for completion and sales. EU Regulation 866/2005	
2005	U.S. Title 24 (California building code) updates take effect Oct 12005. Requires "high efficacy" lights in nearly every room in house. All CFLs must be pin-based, no screw based allowed	
2005	White LED light demonstrates fluorescent efficacy (70 lm/W)	Label LED6
2008	Ushio Lighting demonstrates the first LED filament light bulb	Label LED7
2008	Production white LED light exceeds 100 lm/W	Label LED7
2010	White LED exceeds 150 lm/W	Label LED8
2010	The European Union (including UK) bans the sale of all 100 & 75W incandescent lights. Malaysia bans all 100W incandescents. Australia, Cuba, and the Philippines ban the sale of new incandescents completely.	Labels CFL6 & H6 & ICD8
2011	Philips wins 'L Prize' for LED screw-in lamp equivalent to 60W incandescent A-lamp for general use	Label LED8

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Year	Event	Major event
2011	The European Union (including UK) bans the sale of all 60W incandescent lights. Malaysia bans all 75W incandescents. Argentina bans the sale of new incandescents completely.	Labels CFL6 & H6 & ICD8
2012	The European Union (including UK) bans all incandescent lights greater than 15W. Malaysia bans all 60W incandescents. China, Mexico, and the United States ban the sale of all 100W incandescents. Japan and South Korea ban the sale of new incandescents completely.	Labels CFL6 & H6 & ICD8
2016	Philip's development of the Dubai Lamp defied predictions from the US Department of Energy, which originally claimed that the 200 lumen-per-watt threshold would not be passed until 2025.	Label LED8

Table A9: Timeline of nuclear energy [EIA, 2008b]

Year	Event	Major event
1895	Wilhelm Roentgen, a German physicist, discovered X-rays.	Label 1
1897	J. J. Thomson (England) discovered the electron. In 1906, he received the Nobel Prize in Physics for this discovery.	Label 1
1898	Marie Curie (France), a two-time Nobel Prize winner in Chemistry and Physics, discovered the radioactive elements radium and polonium.	Label 1
1899	Ernest Rutherford (Canada) discovered two kinds of rays emitting from radium. He called the first rays, alpha rays; and the more penetrating rays, beta rays.	Label 1
1900	Frederick Soddy (England) observed spontaneous disintegration of radioactive elements into variants. He called these isotopes.	Label 1
1901	Rutherford and Soddy published the theory of radioactive decay.	Label 1
1905	Albert Einstein wrote the special theory of relativity. He created a new era of physics when he unified mass, energy, magnetism, electricity, and light. One of the most significant events of the 20th century was Einstein's developing the formula of $E = mc^2$ (that is, energy equals mass times the square of the speed of light).	Label 2
1911	Rutherford (United Kingdom) discovered the nucleus of the atom.	Label 3
1913	Niels Bohr (Denmark) published the theory of atomic structure, combining nuclear theory with quantum theory.	Label 3
1915	The general theory of relativity was published by Albert Einstein. He proposed that gravity, as well as motion, could affect the intervals of time and space.	X
1919	Rutherford (United Kingdom) bombarded nitrogen gas with alpha radiation. The transmutation of nitrogen into oxygen was the first artificially induced nuclear reaction.	Label 4
1925	Werner Heisenberg, Max Born (Germany) and later Erwin Schrödinger (Austria) formulated quantum mechanics.	X
1927	Herman Blumgart (United States), a Boston physician, used radioactive tracers to diagnose heart disease.	
1929	Ernest O. Lawrence (United States) conceived the idea for the first cyclotron, a device used to produce high-energy beams for use in nuclear physics experiments. He was awarded the 1939 Nobel Prize in Physics for this invention and for results obtained with it.	X
1929	John Cockcroft and E. T. S. Walton (United Kingdom) developed a high-voltage apparatus for accelerating protons, called a linear accelerator.	X
1932	James Chadwick (United Kingdom) discovered the neutron as well as studying deuterium (known as heavy hydrogen) for use in nuclear reactors.	Label 5
1932	Cockcroft and Walton (United Kingdom) split the atom with protons accelerated with their "linear accelerator".	Label 5
1932	Werner Heisenberg (Germany) was awarded the Nobel Prize in Physics for the creation of quantum mechanics.	

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Table A9 – continued from previous page

Year	Event	Major event
1934	Enrico Fermi irradiated uranium with neutrons. He believed he had produced elements beyond uranium, not realising that he had split the atom, thus achieving the world's first nuclear fission. He won the Nobel Prize in Physics for this discovery in 1938.	Label 5
1938	The process of splitting uranium atoms, called nuclear fission, was demonstrated by scientists Otto Hahn and Fritz Strassman (Germany).	Label 6
1939	President Roosevelt received a letter from Albert Einstein on the possibility of a uranium weapon.	Label 6
1940	German troops occupied Norway, and seized what was then the world's only heavy-water production plant at Vemork.	X
1940	Philip Abelson and Edwin McMillan (United States) demonstrated that neutrons captured by uranium-238 lead to the creation of elements 93 and 94, neptunium and plutonium.	X
1940	A new element (atomic number 94), was found and named plutonium. American physicists confirmed that plutonium was fissionable, thus usable for a bomb.	
1941	British scientists reported that a weapon could be made with 22 pounds of pure uranium 235.	
1942	The Manhattan Project was formed in the United States to secretly build the atomic bomb for use in World War II.	Label 7
1942	The first self-sustaining, controlled nuclear chain reaction led by Enrico Fermi and other scientists at the University of Chicago.	Label 7
1945	The first test of a nuclear weapon, code-named Trinity, occurred at Alamogordo, New Mexico.	Label 7
1945	The United States dropped an atomic bomb on Hiroshima, Japan, and three days later dropped another one on Nagasaki, Japan. Japan surrendered less than two weeks later, ending World War II.	Label 7
1946	The Atomic Energy Act (AEA) of 1946 was passed, establishing the United States Atomic Energy Commission (AEC) to control nuclear energy development and to explore peaceful uses of nuclear energy.	Label 7
1946	First demonstrations against nuclear testing were held in Times Square, New York.	
1946	The Joint Congressional Committee on Atomic Energy was established to oversee all civilian and military nuclear affairs.	Label 7
1946	The Soviet Union achieved its first nuclear chain reaction.	
1949	The Soviet Union detonated its first atomic device.	
1950	President Truman announced the decision to proceed with the development of the hydrogen bomb.	X
1950	Klaus Fuchs confessed to giving atomic secrets to the Soviets while working on the Manhattan Project.	

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Table A9 – continued from previous page

Year	Event	Major event
1951	An experimental breeder reactor (EBR Reactor I, or EBR-I) in Idaho produced the first usable electric power from the atom, lighting four light bulbs. Scientists had already known that nuclear power could produce electricity. The purpose of the experimental EBR was to prove that a breeder reactor could produce more fuel than it used.	Label 8
1953	The first nuclear-powered submarine, the U.S.S. Nautilus, was launched.	Label 8
1953	Eisenhower's Atoms for Peace Program proposed an international agency to develop peaceful nuclear technologies.	Label 8
1953	The first Boiling Reactor Experiment reactor was built in Idaho. It demonstrated that steam bubbles in the reactor core did not cause an instability problem. It was, instead, a rapid, reliable, and effective mechanism for limiting power. This could protect a reactor against "runaway" events.	Label 8
1954	The Atomic Energy Act of 1954 was passed. It was the first major amendment of the original Energy Act, which gave the civilian nuclear energy program further access to nuclear technology.	X
1955	The AEC announced the beginning of a cooperative program between government and industry to develop nuclear power plants.	X
1955	Arco, Idaho, (population 1000) became the first U.S. town powered by nuclear energy. The power was provided by an experimental reactor, BORAX III, at the Idaho National Energy Laboratory.	Label 9
1955	The United Kingdom announced the decision to develop thermonuclear weapons.	
1955	The United Nations sponsored the first international conference on the peaceful uses of nuclear energy, held in Geneva, Switzerland.	Label 9
1956	The world's first commercial nuclear power station, Calder Hall at Windscale, England, was opened in 1956 with an initial capacity of 50 MW (later 200 MW).	Label 9
1957	The first time that power was generated from a U.S. commercial nuclear plant, at Santa Susana, California.	Label 9
1957	The Price-Anderson Act enacted. This legislation was designed to limit the financial risk of nuclear plant owners in the event of an accident.	
1957	The first full-scale nuclear power plant in the U.S. (Shippingport, Pennsylvania) began service.	
1957	The International Atomic Energy Agency (IAEA) was formed with 18 member countries to promote peaceful uses of nuclear energy and to prevent the spread of nuclear weapons.	Label 9
1957	The Soviet Union launched the first nuclear-powered surface ship, the Lenin.	Label 9
1957	10th October: Windscale fire: A fire at the British atomic bomb project destroyed the core and released an estimated 740 terabecquerels of iodine-131 into the environment. A rudimentary smoke filter constructed over the main outlet chimney successfully prevented a far worse radiation leak and ensured minimal damage.	Label 9

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Table A9 – continued from previous page

Year	Event	Major event
1958	President Eisenhower signed amendments to the 1954 Atomic Energy Act, which led to a bilateral agreement between the United Kingdom and the United States on nuclear weapon design information.	
1958	From November 1958 to September 1961, the United States, the United Kingdom, and the former Union of Soviet Socialist Republics (USSR) observed an informal moratorium on nuclear tests.	
1959	The United States deployed the first operational intercontinental ballistic missile (ICBM), the Atlas D.	
1960	The AEC published its 10-year plan for nuclear energy.	
1960	Small nuclear power generators were first used in remote areas to power weather stations and to light buoys for sea navigation.	
1962	The first nuclear-powered merchant ship, the N.S. Savannah, was put to sea. Developed as part of President Eisenhower's Atoms for Peace Program, the Savannah was christened by Mrs. Dwight D. Eisenhower in 1959.	X
1964	President Lyndon Johnson signed the Private Ownership of Special Nuclear Materials Act of 1964, which allowed the nuclear energy industry to own the fuel for its units. After June 30, 1973, private ownership of the uranium fuel became mandatory.	
1964	The U.S. Navy sent three nuclear-powered surface ships (Enterprise, Long Beach and Bainbridge) on an around-the-world cruise to show their ability to operate away from land bases.	X
1964	The AEC issued a construction permit for Oyster Creek nuclear power plant.	
1965	The first nuclear reactor, a 500-watt system, operated in space. It operated for 43 days and remains in orbit.	X
1965	The AEC gave the liquid metal fast breeder reactor highest priority and decided to build the Fast Flux Test Facility.	
1965	The first major electrical blackout occurred in the north-eastern United States.	
1968	The Treaty on the Non-Proliferation of Nuclear Weapons, also known as the Nuclear Non-Proliferation Treaty (NPT), was adopted. The treaty called for halting the spread of nuclear weapon capabilities.	X
1970	The First Earth Day was celebrated.	
1970	Electricity "brownouts" hit the North-east during a heat wave. A "brownout" is a reduction or cutback in electric power, especially as a result of a shortage, mechanical failure, or overuse by consumers.	
1971	President Nixon announced a U.S. national goal of completing the liquid metal fast breeder reactor by 1980.	Label 10
1973	President Nixon proposed replacing the Atomic Energy Commission with the Energy Research and Development Administration and the Nuclear Regulatory Commission.	

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Table A9 – continued from previous page

Year	Event	Major event
1973	The Arab Oil Embargo occurred, in which several Arab nations in the Organization of Petroleum Exporting Countries (OPEC) embargoed oil to the United States and Holland to protest their support of Israel in the Arab-Israeli "Yom Kippur" War. Arab OPEC production was cut by 25%, which caused some temporary shortages and helped oil prices to triple. This contributed to an increased interest in alternatives to petroleum, including nuclear power.	Label 10
1973	U.S. utilities ordered 41 nuclear power plants, a one-year record.	
1974	The first 1000-megawatt nuclear plant went into service (Commonwealth Edison's Zion Nuclear Power Plant, Unit 1).	Label 10
1974	The Atomic Energy Commission was abolished in the U.S., and the Nuclear Regulatory Commission (NRC) was created to regulate the nuclear industry. The Joint Congressional Committee on Atomic Energy was also abolished.	
1975	The Energy Research and Development Administration began operating in the U.S.	
1977	U.S. President Carter combined the Energy Research and Development Administration with the Federal Energy Administration, creating the Department of Energy.	
1977	The Voyager 2 spacecraft was launched into space. The spacecraft's electricity was generated by the decay of plutonium pellets.	
1979	The accident at the Three Mile Island Unit 2 (TMI-2) nuclear power plant near Middletown, Pennsylvania, on 28th March, 1979, was the most serious in the U.S. nuclear power plant industry's operating history. Equipment malfunctions, design-related problems, and human error led to led to a partial meltdown of the TMI-2 reactor core but only very minute releases of radioactivity. Although no deaths or injuries resulted, the accident brought about sweeping changes in emergency response planning, reactor operator training, human factors engineering, radiation protection, and many other areas of nuclear power plant operations. These changes enhanced the safety of the industry.	Label 11
1979	The U.S. nuclear energy industry created the Institute of Nuclear Power Operations to address issues of safety and performance.	
1979	Completing a process begun by President Ford, President Carter banned the use of reprocessed uranium in nuclear fuel. The ban's purpose was to prevent the used fuels from falling into the wrong hands and being used for nuclear weapons.	
1980	For the first time, nuclear energy generated more electricity than oil in the United States.	X
1981	President Ronald Reagan lifted the ban on reprocessing used nuclear fuel.	
1983	The Nuclear Waste Policy Act of 1982 was signed, approving the development of a high-level nuclear waste repository.	
1983	Nuclear energy generated more electricity than natural gas.	X
1984	Nuclear replaced hydropower as the second-largest source of electricity in the United States, after coal.	X

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Table A9 – continued from previous page

Year	Event	Major event
1986	The Perry power plant in Ohio became the 100th U.S. nuclear power plant in operation.	
1986	The world's worst nuclear power accident happened at the Chernobyl plant in the former USSR (now Ukraine).	Label 12
1987	Congress selected Yucca Mountain in Nevada for study as the first high-level nuclear waste repository site.	
1989	Nuclear power plants provided 19% of the electricity used in the United States; 46 units entered service during the 1980s.	
1992	The Energy Policy Act of 1992 reformed the licensing process for nuclear power plants.	
1993	Two decades after the first oil embargo, the 109 nuclear power plants operating in the United States provided about one-fifth of the nation's electricity.	
1994	The Nuclear Regulatory Commission (NRC) issued final design approval for the first two of four advanced nuclear power plant designs — General Electric's Advanced Boiling Water Reactor (ABWR) and ABB Combustion Engineering's System 80+.	
1996	The NRC granted the Tennessee Valley Authority (TVA) a full-power licence for its Watts Bar 1 nuclear power plant. This was the last unit to be licenced in the United States in the 20th century.	
1996	Kashiwazaki-Kariwa 6, the world's first Advanced Boiling Water Reactor, began commercial service in Japan.	Label 13
1997	The NRC issued General Electric design certification for its Advanced Boiling Water Reactor.	
1998	Baltimore Gas and Electric Co. submitted an application to renew the licence of its two-unit Calvert Cliffs nuclear power plant—the first U.S. company to apply for a 20-year extension of its 40-year licence.	
2000	The NRC issued the first-ever licence renewal to Constellation Energy's Calvert Cliffs Nuclear Power Plant, allowing an additional 20 years of operation.	
2000	The NRC approved a 20-year extension to the operating licence of Duke Energy's three-unit Oconee Nuclear Station.	
2001	The U.S. National Energy Plan was published in May 2001. The Plan included a significant role for nuclear power in meeting energy demand and for reducing air pollution levels.	
2002	The U.S. Nuclear Power 2010 Program, developed in 2002, was a joint government/industry cost-shared effort to identify sites for new nuclear power plants, develop and bring to market advanced nuclear plant technologies, evaluate the business case for building new nuclear power plants, and demonstrate untested regulatory processes.	Label 14
2002	30th April: the oldest nuclear power plant in the world, Obninsk (located in Russia), closed down its sole reactor.	X
2002	Nuclear power provided about 16% of the world's electricity.	

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Table A9 – continued from previous page

Year	Event	Major event
2003	14th August: the Unites States' largest-ever power outage left much of the North-east and parts of Canada without electricity for several days. A transmission line in Ohio strained the electrical system so much that plants all over the grid, including nine U.S. and eight Canadian commercial nuclear reactors, were shut down.	
2004	The British Nuclear Group announced the closing of the Chapelcross nuclear power plant, one of the world's oldest plants.	
2005	3rd January: Lithuania, the world's most nuclear-dependent nation, began the complete and final shut-down of one-half of its nuclear capacity. Lithuania's nuclear reactors are being shut-down owing to safety concerns. They have the same design as the reactors at Chernobyl, the site of the world's worst nuclear accident.	
2005	The Polish Government decided to build the Nation's first nuclear power plant.	
2005	8th August: President Bush signed the Energy Policy Act of 2005, which included measures to encourage the nuclear industry to build new nuclear power plants. (No construction of a nuclear plant has begun since 1971.)	
2006	A survey, in the United States, found a high level of support for nuclear energy among the public; with 68% favouring nuclear energy as one way to generate electricity and 49% stating a need to build more nuclear plants.	
2007	Browns Ferry Nuclear Power Plant Unit 1 was the first U.S. nuclear reactor to come online in the 21st century. Shut down in 1985, the Tennessee Valley Authority (TVA) decided in 2002 to restart the unit. It had the capacity to supply electricity to about 650000 homes.	
2011	The Fukushima Daiichi nuclear disaster is initiated primarily by the tsunami following the Tohoku earthquake on 11 March 2011. The Fukushima Power Plant disaster was the most significant nuclear incident since April 26, 1986 the Chernobyl disaster and the second disaster to be given the Level 7 event classification of the International Nuclear Event Scale.	Label 15

Table A10: Timeline of printing technologies
[Clymer and Asaba, 2008, Leurs, 2018, Kelleher, 2012, Yarin, 2018, Agrawal and Dwoskin, 2003b]

Year	Event	Major event
3000 BC and earlier	The Mesopotamians use round cylinder seals for rolling an impress of images onto clay tablets. In other early societies in China and Egypt small stamps are used to print on cloth. These stamps are gradually replaced by larger wooden blocks. In China such woodblocks are used to print on silk. The earliest known examples consist of flowers printed in three colours. They are likely produced during the Han dynasty (before 220 BC).	
2600-2000 BC	First printing plates: The printing plates discovered are still being investigated. If they are genuine, the Harappan civilization in the Indus Valley is the first one to use fairly modern printing techniques. One of the plates bears 34 characters, which is the longest known single Indus script inscription.	
131 BC	First newspapers: The first Acta Diurna (Latin for 'Daily Acts') are published in Rome in 131 BC. These are daily official notices of the Roman Empire and can be considered the first 'newspaper'. The notices are carved on stone or metal, they do not get printed. Scribes sometimes do make copies to be sent to the provinces.	
2nd century	Paper is invented: A Chinese man named Ts'ai Lun is credited with inventing paper around 105 AD. He takes the inner bark of a mulberry tree and bamboo fibres, mixes them with water, and pounds them with a wooden tool. This mixture is poured onto a flat piece of coarsely woven cloth and let the dry, leaving only the fibres on the cloth. From China the knowledge of paper making is passed along to Korea, Samark Baghdad and Damascus.	
7th century	Oldest European book: In 687 a small book containing the text of the Gospel of John in Latin is added to the grave of Saint Cuthbert. In 1104 it is recovered from his coffin in Durham Cathedral, Britain. The Cuthbert Gospel is currently the oldest European book still in existence.	
8th century	Paper making reaches the Arabic world: During the Battle of Talas, near Samarkand in 751 AD, the secret of paper production is made known to the Islamic world, as some of the Chinese prisoners are paper makers.	
9th century	First printed book: A copy of the Chinese version of The Diamond Sutra (or Diamond Cutter of Perfect Wisdom) is the earliest surviving example of a printed book. It is produced in 868 AD using woodcut, a relief printing technique in which text and images are carved into the surface of a block of wood. The printing parts remain level with the surface while the non-printing parts are removed, typically with a knife or chisel. The wood block is then inked and the substrate pressed against the wooden block.	
10th century	Invention of screen printing: During the Shang Dynasty the Chinese invent screen printing.	
10th century	Arabs create a finer sheet of paper by substituting linen fibres for wood and bamboo.	

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Table A10 – continued from previous page

Year	Event	Major event
11th century	Invention of movable type: In 1023 the Chinese emperor establishes a Bureau of Exchange which is charged with issuing what can be considered the first government-issued banknotes. Chinese merchants had already been issuing banknotes themselves since the Tang Dynasty (618–907).	
11th century	A Chinese man named Bi Sheng (or Pi-Sheng, depending on the source) develops type characters from hardened clay, creating the first movable type in 1041. The fairly soft material hampers the success of this technology.	
12th century	Around 1150 the first European paper mill is established in Xàtiva, a city in Spain. Since paper is mainly produced by Muslims it is frowned upon and there are even laws that forbid the use of paper for government documents.	
13th century	Since books are copied by hand, they are rare and expensive. A copy of Justinian's lawcodes costs £40 in 1240, which is as much as a house or eight year's income for a craftsman.	
13th century	In 1282 watermarks appear for the first time when they are added to paper in Fabriano, Italy.	
14th century	Type characters cast from metal (bronze) are developed in Japan and China. The oldest known book printed using metal type dates to the year 1377. It is a Korean Buddhist document, called Selected Teachings of Buddhist Sages and Seon Masters.	
1424	Books are still rare since they need to be laboriously handwritten by scribes. The University of Cambridge has one of the largest libraries in Europe – constituting of just 122 books.	
1430	First woodcut printing on paper: Even though woodcut is already used for printing on cloth for over a century, the first European woodcut printing on paper happens in the early 15th century. It is used for printing religious images and playing cards. Woodcut is a relief printing technique in which text and images are carved into the surface of a block of wood. The printing parts remain level with the surface while the non-printing parts are removed, typically with a knife or chisel. The wood block is then inked and the substrate pressed against the wood block. The ink is made of lampblack (soot from oil lamps) mixed with varnish or boiled linseed oil. This printing technique is also called block printing. The first block books are produced in Germany and Holland around 1430.	
1436	Gutenberg starts working on a printing press: It takes him four years to finish his wooden press which uses movable metal type. It uses relief printing: at the bottom a frame holds the columns of text that get printed. This type consists of individual letters set in lead. After inking the type, a sheet of paper is put on top. Next, the frame is shoved to the right underneath the platen. By moving the large handle pressure is applied to make sure the ink is transferred to the paper. Afterward, the bed is moved back to its original position and the paper can be removed.	
1448	Gutenberg sets up a printing shop in Mainz: Among his first publications printed using movable type are the 'Poem of the Last Judgment' and the 'Calendar for 1448'. Around 1450 Gutenberg begins printing bibles. The first edition has 40 lines per page.	

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Table A10 – continued from previous page

Year	Event	Major event
1453	Constantinople is captured by the Turks. Many books from the Constantine library are burnt or carried away and sold.	
1455	Gutenberg Bible: Gutenberg prints around 180 copies of a 42-line bible which is referred to as the Gutenberg Bible. It is considered the first mass produced book. The text is set in Gothic type. Customers can have their copy decorated manually.	
1455	Ironically enough Gutenberg goes bankrupt in 1455 when his investor Johann Faust forecloses on the mortgage used to finance the building of the press. Faust gets hold of the printing equipment as well as the copies of the bible that have already been printed. While trying to sell them in Paris Faust tries to keep the printing process a secret and pretends the bibles are hand copied. It is noticed that the volumes resemble each other and Faust is charged with witchcraft. He has to confess his scheme to avoid prosecution.	
1457	First colour printing: The first known colour printing is used in 'Mainz Psalter', a book containing a collection of psalms. It is printed by Johann Faust and his son-in-law Peter Schoffer.	
1461	First books with woodcut illustrations: Albrecht Pfister prints the first illustrated books using a number of woodcuts that are coloured in manually. Another of his books, the Biblia Pauperum, also contains many hand coloured illustrations. Pfister is also one of the first to print books in the German language.	
1465	The first drypoint engravings are created by the Housebook Master, a south German artist. Drypoint is a technique in which an image is incised into a (copper) plate with a hard-pointed 'needle' of sharp metal or a diamond point.	
1467	First Italian books: The first book is printed in Rome by Ulrich Haan (Udalricus Gallus). Haan had emigrated to Rome after his letterpress print shop in Vienna was destroyed because he had dared to print a lampoon against the mayor.	
1469	Use of roman type: In their print shop in Venice John and Wendelin of Speier are probably the first printers to use pure roman type, which no longer looks like the handwritten characters that other printers have been trying to imitate until then. Another printer in Venice, Nicolas Jenson, produces a more distinguished roman font which still serves as a model for type designers today.	
1470	First book in Italian language: Il Canzoniere by Francesco Petrarca is the first book printed in the Italian language.	
1472	Book printing takes off in Spain: Sinodal de Aguilafuente is the first book printed in Spain and in the Spanish language. Its printing was ordered by the bishop of Segovia, which is why printing did not take off first in any of the major Spanish cities, like Barcelona or Madrid.	
1475	'De honesta voluptate' (On honourable pleasure) is one of the first printed cookbooks. It is as much a series of moral essays as a cookbook. Ten years later 'Kuchenmeysterey' (Kitchen Mastery) becomes the first printed German cookbook.	

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Table A10 – continued from previous page

Year	Event	Major event
1476	William Caxton introduced metal type in England: William Caxton buys equipment from the Netherlands and establishes the first printing press in England at Westminster. Books printed by Caxton include Chaucer's 'The Canterbury Tales', 'Fables of Aesop' and many other popular works. Caxton is also the first English retailer of printed books.	
1476	That same year copper engravings are for the first time used for illustrations. With engravings, a drawing is made on a copper plate by cutting grooves into it.	
1481	There are around 40 printing shops in both Germany and Italy. In the Netherlands printing takes place in 21 cities and towns.	
1489	First print shop in Denmark: Dutch printer Gotfried van Os (Gotfred of Ghemen) establishes the first print shop in Copenhagen.	
1493	The Nuremberg Chronicle: Anton Koberger, a publisher and printer in Nuremberg, prints his most famous book, the 'Nuremberg Chronicle'. It is illustrated with hundreds of woodcuts, many of them portraits. These portraits are all imaginary and the same block is often used to depict different persons.	
1494	Das Narrenschiff: Das Narrenschiff (The Ship Of Fools) by Sebastian Brant is published in Basel, Switzerland. This satire about the state of the church is illustrated with woodcuts from the great Renaissance artist-engraver Albrecht Dürer. It quickly becomes extremely popular, with six authorised and seven pirated editions published before 1521.	
1495	The first printed books are published in Danish and Swedish.	
1499	Printing has become established in more than 250 cities around Europe. Renaissance printing presses can produce 3600 pages per workday, compared to forty by typographic hand-printing and just a few pages by hand-copying. One of the main challenges of the industry is distributing all these works. This leads to the establishment of numerous book fairs. The most important one is the Frankfurt Book Fair which is first held by local booksellers soon after Gutenberg's invention of the printing press. Frankfurt remains the book capital of the world until the end of the 17th century when the Leipzig Book Fair takes over. After World War II the Frankfurt Book Fair is re-established and regains its position as the world's largest trade show for books.	
1500	Early aerial map: Painter and engraver Jacopo de' Barbari publishes a huge 1.3 by 2.8 metre aerial map of Venice, printed using six woodcut blocks. It took him three years to create the spectacular bird's eye view. The map is so detailed historians still use it today to study 16th century Venice.	
1502	Aldus Manutius is the first printer to come up with smaller, more portable books. Until then books are large and heavy, meant to be read while standing at a lectern or reading stand. Manutius's books are smaller and can be carried around and read anywhere. Manutius was also the first to use Italic type, designed by Venetian punchcutter Francesco Griffo.	

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Year	Event	Major event
1507	Chiaroscuro: Lucas Cranach invents the chiaroscuro woodcut, a technique in which drawings are reproduced using two or more blocks printed in different colours. The Italian Ugo da Carpi is one of the printers to use such woodcuts, for example in Diogenes. In Germany, the technique peaks around 1520, but in Italy, this early form of colour printing remains in use throughout the sixteenth century.	
1522	Scribes still publish manuscripts: Even though movable type revolutionised book production, some types of works are still done by scribes. The Tsgrooten Antiphonary is a beautiful example of a hymn book that is created and decorated by hand.	
1525	Dürer engravings: The famous painter, wood carver and copper engraver Albrecht Dürer publishes 'Unterweysung der Messung' (A Course on the Art of Measurement), a book on the geometry of letters.	
1543	Vesalius anatomy books: De humani corporis fabrica libri septem (On the fabric of the human body in seven books) is a book of human anatomy written by Andreas Vesalius. It combines text with numerous illustrations and shows how much printing has evolved during this era.	
1548	Pocket atlas: In Venice Giacomo Gastaldi publishes Geography, the first pocket atlas. It is one of the first books to show regional maps of the Americas.	
1551	The Historia Veneta (History of Venice) is one of the many books of Pietro Bembo, a Venetian scholar and cardinal who is most famous for his work on the Italian language and poetry. The Bembo typeface is named after him.	
1555	Christophe Plantin is one of the most famous printers of his time. In his print shop in Antwerp, he produces fine work ornamented with engravings after Rubens and other artists.	
1555	The publishing and printing company of Plantin and his son-in-law Jan Moretus remains in business until 1867. Nowadays it is a museum with an interesting collection of old presses, type and books.	
1568	Jost Amman's woodcuts in Der Buchdrucker (The Printer) show how books are produced in this era.	
1582	First specimen type book: Willem Silvius is a printer in Antwerp who publishes the earliest known type specimen book in the low countries, the Leyden Afdrucksel.	
1605	First newspaper: Relation aller Fürnemmen und gedenckwürdigen Historien, which is printed from 1605 onwards by Johann Carolus in Strasbourg, is considered the first newspaper. That same year the first German newsletter, the Avisa, is published.	
1620	Invention of the Dutch press: In Antwerp Abraham Verhoeven publishes the first regularly illustrated newspaper. Nieuwe Tijdinghen (New Tidings) is also the first paper to print a headline on the front page.	

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Table A10 – continued from previous page

Year	Event	Major event
1620	Meanwhile in Amsterdam cartographer, publisher and printer Willem Janszoon Blaeu improves the printing press by adding a counterweight to the pressure bar so that the platen rises automatically. The revised design, called the 'Dutch Press', largely remains in use until Stanhope introduces an iron cast press.	
1622	The Weekly Newes from Italy is the first news book to carry the date of publication on its title page.	
1626	The first facsimile: Plantin Press prints the first facsimile, a copy of the 16th century 'Martyrologium Hieronymianum' which gets engraved on copper plates. A facsimile is a reproduction of an old book, manuscript, map, art print or another item that is as true to the original source as possible.	
1631	Most famous typesetting error: The word 'not' is accidentally left out of Exodus 20:14 in a reprint of the King James Bible. King Charles I and the Archbishop of Canterbury are not amused when they learn that God commanded Moses 'Thou shalt commit adultery'. The printers, Robert Barker and Martin Lucas, are fined and have their printing licence revoked. The King orders all bibles to be destroyed but eleven still exist today. This version of the Bible is referred to as The Wicked Bible and also called the Adulterous Bible or Sinner's Bible.	
1640	In Paris, the Imprimerie Royale du Louvre is established at the instigation of Richelieu. The first book that is published is 'De Imitatione Christi' (The Imitation of Christ), a widely read Catholic Christian spiritual book that was first published in Latin around 1418.	
1640	In 1640 the Bay Psalm Book becomes the first book printed in British North America. Only eleven copies are known to exist from the first edition, one of them getting sold for $14.2 million at an auction in 2013.	
1642	Mezzotint: Ludwig von Siegen invents mezzotint, a technique to reproduce halftones by roughening a copper plate with thousands of little dots made by a metal tool with small teeth, called a 'rocker'. The tiny pits in the plate hold the ink when the face of the plate is wiped clean.	
1661	First printed banknotes: The first European banknotes are issued in Sweden by Stockholms Banco, the precursor to Sveriges Riksbank – the central bank of Sweden. Each note was hand signed by 16 prominent and trustworthy officials to overcome objections that paper money would lead to the downfall of the Swedish monetary system.	
1660	Klencke Atlas: Joan Klencke create an atlas measuring 1.78 by 1.05 metre. It remains the largest atlas of the world until 2012 when the Earth Platinum atlas is published. A group of Dutch merchants donate the Klencke Atlas to King Charles II of England as a gift for restoring the monarchy.	

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Table A10 – continued from previous page

Year	Event	Major event
1662	Atlas Maior, the most expensive atlas ever: Joan Blaeu, son of Willem Janszoon Blaue, publishes the most expensive printed book of the seventeenth century, the Atlas Maior. The Dutch version consists of 9 and the French version of 12 volumes. The richly decorated atlas contains eleven volumes, 600 double-page maps and 3000 pages of text. The most expensive coloured edition cost around $ 40000 in today's money.	
1690	The first American paper mill is established.	
1692	Lloyd's News: Lloyd's News is the forerunner of Lloyd's List, a journal containing maritime news. It is one of the world's oldest continuously-running journal. Issue 60850 from 2013 was the last one to appear in print. Since then it has become a digital publication.	
1702	The first daily newspaper: The Daily Courant is the first British daily newspaper. The single page two column newspaper only focusses on foreign news. It has advertisements on the reverse side and is published until 1735 when it merges with the Daily Gazetteer.	
1704	The Boston News-Letter: The Boston News-Letter is the first newspaper that is published on a continuous basis in British North America. It is subsidised and controlled by the British government and has only limited circulation.	
1709	First modern copyright legislation: The Statute of Anne is the first modern copyright law. It originates in the United Kingdom.	
1710	Colour engravings: The German painter and engraver Jakob Christof Le Blon produces the first engraving in several colours. He uses the mezzotint method to engrave three metal plates. Each plate is inked with a different colour, using red, yellow and blue. Later on, he adds a fourth plate, bearing black lines. This technique helped form the foundation for modern colour printing. Le Blon's work is based on Newton's theory, published in 1702, which states that all colours in the spectrum are composed of the three primary colours blue, yellow and red.	
1716	William Caslon is an English typographer whose foundry operates in London for over 200 years. His Caslon Roman Old Face is cut between 1716 and 1728. The letters are modelled on Dutch types but they are more delicate and not as monotonous. Caslon's typefaces remain popular, digital versions are still available today.	
1721	The New England Courant is published by James Franklin, the older brother of Benjamin Franklin. The market for such newspapers is still very limited with press runs (the total number printed) of 300 or less.	

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Table A10 – continued from previous page

Year	Event	Major event
1725	Duplicating printing plates using stereotyping: The Scottish goldsmith William Ged invents stereotyping. In this process, a mixture of plaster is poured on a tray of completed type to make a mould from it. Hot metal is poured into this mould and allowed to set. The resulting stereotype or cliché is a printing plate that is an exact copy of the original. From 1848 onwards moulds are created from papier-mâché instead of plaster. The stereotyping process makes larger press runs as well as reprints much cheaper. It is used extensively for printing books and newspapers until the late 1800s when it is gradually getting replaced by electrotyping which delivers sharper copies in which finer detail can be preserved.	
1727	Miniature bibles: In London the Biblia or 'a Practical Summary of ye Old & New Testaments' is printed. This tiny 4 by 3-centimetre shortened version of the Bible is bound in leather with reliefs. It contains 284 pages with 14 wood engravings. Tiny books like this are popular collector's items to this day.	
1731	The first magazine: The Gentleman's Magazine, considered to be the first general interest magazine, is published for the first time. The publication runs uninterrupted until 1922.	
1732	Poor Richard's Almanac: In the American colonies Benjamin Franklin, who had learned to print from his brother, establishes his own printing office and becomes the publisher of the Pennsylvania Gazette. Among his publications, Poor Richard's Almanac, a yearly publication containing a calendar, weather, poems, sayings and astronomical and astrological information, becomes the most famous. He sells the business again in 1748 to devote his time to his literary, journalistic and civic activities. He does keep promoting the print industry in the colonies.	
1760s	The first jigsaw puzzles: English cartographer John Spilsbury starts making jigsaw puzzles of engraved maps. These were used as teaching tools, alongside map board games which J. Jeffreys had started producing a few years before.	
1765	Rise of American newspapers: The average press run of American newspapers has risen to between 600 and 800. The aggregate circulation of all newspapers in America is estimated to be 14000 on a weekly basis.	
1772	Patents for coloured inks: In England, the first patent is issued for making coloured inks. Full colour printing, as we know it today, is still a far way off as the pigments of those inks are not pure.	

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Table A10 – continued from previous page

Year	Event	Major event
1796	Invention of lithography: Alois Senefelder invents lithography and uses it as a low-cost method for printing theatrical works. Lithography is a printing technique in which an image is drawn on a stone (a lithographic limestone) using a coating of wax or another greasy substance. This makes those areas hydrophobic (water repellent but ink accepting) while the slightly roughened remaining parts are hydrophilic (water accepting). The stone is then moistened with water which the hydrophilic parts suck up. Next, an oil-based ink is rolled onto the stone. Only the greasy parts pick up the ink. Finally, a piece of paper is pressed onto the stone and the ink transfers from the stone to the paper. Lithography is still the dominant printing technique today. Meanwhile, the stone has been replaced by an aluminium or plastic plate and the image to be printed is created digitally, not by hand.	
1798	Giambattista Bodoni creates a series of typefaces that carry his name and that are still frequently used today. They are characterised by the sharp contrast between the thick vertical stems and thin horizontal hairlines.	
1798	Initially, Bodoni ran a state-owned printing house in Parma, Italy but his success enabled him to start his own company, Officina Bodoni. During his lifetime Bodoni designed and engraved 298 typefaces. A facsimile of Il Manuale tipografico (The Manual of Typography), which shows many of his designs, is still available today.	
1799	Invention of the paper making machines: The Frenchman Louis-Nicolas Robert invents a continuous paper making machine, based on a specially woven bronze mesh conveyor belt called 'the wire'. An improved version is developed by his financial backers, the English brothers Sealy and Henry Fourdrinier whose Fourdrinier Machines become operational from 1803 onwards. Pulp, made from linen or hemp rags, is poured on a woven wire conveyor belt. Water leaks away through the belt. Heated rollers smooth and dry the paper which is then rolled up. Modern papermaking machines are still based on this concept.	
1800	Iron presses: Charles Stanhope, the third Earl Stanhope, builds the first press which has an iron frame instead of a wooden one. It can print around 200 impressions per hour. Because this Stanhope press is also more durable and can print larger sheets, other press manufacturers soon switch to a similar type of construction.	
1810	History of Printing in America: Isaiah Thomas creates the two-volume History of Printing in America which is one of the best resources on colonial printing in the United States.	
1814	First cylinder presses: Friedrich Gottlob Koenig and Andreas Friedrich Bauer build their first cylinder press, which is much faster than the existing flatbed presses. One of the first customers is John Walter of The Times. The first issue of The Times that is printed with the new presses is published in 1814. The press is installed in secret to avoid sabotage by disgruntled pressmen operating the existing Stanhope presses. The machine is capable of printing over 1100 double-sided sheets per hour. In 1817 Koenig & Bauer return to Germany and start building presses in an abandoned monastery in Würzburg. Their company is nowadays known as KBA.	

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Table A10 – continued from previous page

Year	Event	Major event
1816	Columbian Press: The cast iron Columbian Press, invented by George Clymer, can produce 250 prints per hour. The Eagle mounted on top is not just a decorative element, it also serves as a counterweight.	
1817	Cardboard boxes: The first cardboard box packaging is produced. The Kellogg Company is the first to use it for packaging cereals in the late 19th century.	
1826	Dandy roll: John Marshall invents the dandy roll which makes it much easier for paper manufacturers to add a watermark to paper.	
1827	Baedeker travel guides: Verlag Karl Baedeker is founded by Karl Baedeker. It publishes travel guides and becomes such a household name that such guides are often referred to as 'Baedekers'.	
1827	That same year Rudolphe Töpffer creates the world's first comic strip in Switzerland.	
1829	Braille is invented: Louis Braille publishes his Braille alphabet, a tactile reading system for the blind.	
1832	Automating binding: Philip Watt invents the sewing machine, a major step forward in automating binding.	
1837	Chromolithography: In France, Godefroy Engelmann is awarded a patent on chromolithography, a method for printing in colour using lithography. Chromolithographs or chromos are mainly used to reproduce paintings. In the United States, A. Hoen & Co in Baltimore is one of the first printing companies to use the technology.	
1840	The first adhesive postage stamp: The Penny Black is the first adhesive postage stamp. It allows UK citizens to send letters of up to 14 grams to any location in the country at a flat rate of one penny.	
1841	Anastatic printing: Anastatic printing is a process to create a facsimile or identical copy of a document. As such, it is an early forerunner of photocopying. Its most well-known proponent is Edgar Allan Poe, the American poet and writer who publishes an article on the potential and dangers of the technique.	
1842	The first illustrated weekly newspaper: The Illustrated London News is the world's first illustrated weekly newspaper. It costs five pence. From 1861 onwards such newspaper becomes a lot cheaper in the United Kingdom because of the abolition of paper duty.	
1843	First use of photos in a book: Photographs of British Algae: Cyanotype Impressions by English botanist and photographer Anna Atkins is the first book ever to be illustrated exclusively with photographs. The 389 photos are all made by placing algae directly onto photographic paper and exposing them using sunlight.	
1843	Printed Christmas cards: Sir Henry Cole commissions the English painter John Callcott Horsley to do the artwork of (arguably) the first commercial Christmas card. Around 1000 cards are printed and hand-coloured. Ten of these are still in existence today. The card was fairly controversial in its day because it featured a child taking a sip from a glass of wine.	

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Year	Event	Major event
1843	That same year the American inventor Richard March Hoe builds the first lithographic rotary printing press, a press in which the type is placed on a revolving cylinder instead of a flatbed. This speeds up the printing process considerably. Printing gets even faster in 1870 when Hoe builds a rotary press that prints both sides of a page in a single operation. This roll-fed press has a speed of 240 metres (800 ft) per minute. It is used for printing newspapers and includes a built-in cutting unit and separate folder.	
1844	Using wood to produce paper: The Canadian inventor Charles Fenerty and his German counterpart F.G. Keller simultaneously invent a new papermaking technique based on pulping wood. Until then all paper was made from pulped rags. Cotton fibre is still used today but only for speciality applications such as currency.	
1844	Carl Buz and Carl August Reichenbach, a nephew of Friedrich Koenig, establish the Reichenbach'sche Maschinenfabrik and build their first press, the 'Schnellpresse'. Their factory will later become a part of Manroland, currently one of the largest manufacturers of printing presses.	
1846	Five daily newspapers in New York City create The Associated Press (AP) to share the cost of transmitting news of the Mexican-American War by boat, horse express, and telegraph. Other news agencies from the same era are Agence France-Presse or AFP (France, 1835), Agenzia Stefani (Italy, 1853) and Reuter's Telegram Company (UK, 1857).	
1846	Friedrich von Martini begins manufacturing folding and stitching machines. Martini introduced its Book Sewing Machine in 1897 and for 37 years also builds automobiles. It is now part of Muller Martini.	
1858	Gordon Jobber: George Phineas Gordon produces the Franklin press, which is also known as the Gordon Jobber. Once the patents on this design expired other companies build presses based on Gordon's design, such as the Chandler & Price letterpress.	
1860	Photozincography: A reproduction of the Domesday Book is the first publication that is printed using photozincography, a lithographic printing technique that uses zinc plates instead of stones. It is developed by the team of Henry James of the British Ordnance Survey. These plates are the precursor to today's aluminium offset printing plates.	
1865	Faster web presses: William Bullock perfects Hoe's rotary press. His web press prints on both sides, folds the paper and cuts sheets at a speed of up to 12000 sheets an hour. Bullock dies during an operation to amputate his leg that accidentally got crushed in one of his presses.	
1867	Agfa, the Aktiengesellschaft fur Anilinfabrikation, is founded in Rummelsburg, Germany. Originally the company focuses on producing colour dyes but it will gradually become one of the leading manufacturers of film and printing plates.	
1874	Production of corrugated board: Mass production of corrugated board starts. It is initially used to package bottles and glass lantern chimneys.	

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Year	Event	Major event
1875	Printing on tin: In England, Robert Barclay patents the first rotary offset lithographic printing press for printing on tin. As the name offset implies, in this press the tin substrate does not come into direct contact with the printing cylinder. In between is an offset cylinder covered with specially treated cardboard that transfers the printed image to the recipient. Cardboard later gets replaced by rubber, which is still the most commonly used material today.	
1876	Duplicating documents with the Mimeograph: Thomas Edison receives a patent for a printing mechanism that around 1890 will result in the mimeograph or stencil duplicator. The Mimeo name is a trademark of Albert Blake Dick who licences Edison's patents. European manufacturers such as Gestetner develop similar machines. They allow anyone to inexpensively print dozens or hundreds of copies of a typed page. These small duplicators remain popular until photocopying becomes affordable.	
1876	Wilhelm Koenig designs the first KBA web-fed rotary press. It is installed at the Magdeburgische Zeitung. By 1895 the company delivers its 5000th cylinder press.	
1876	Golding & Co. introduce the Pearl letterpress, a small printing press that is available in two sizes. It has no throw-off or depressible grippers and two ink rollers. The press sells well but many commercial printers only consider it suitable for 'bedroom printers'.	
1878	Invention of photogravure: The Czech painter Karel Klíc invents photogravure, a process to faithfully reproduce the detail and continuous tones of photographs. To do so a copper plate is coated with a light-sensitive gelatin tissue which has been exposed to a film positive. The plate is then etched so that when ink is applied to the plate and wiped off, some ink will remain in the etched grooves and can then be transferred to paper.	
1883	First British photogravure: T. & R. Annan in Glasgow is the first photogravure in Britain.	
1884	Mechanical sewing machines: Hugo Brehmer develops the first mechanical thread-based sewing machine for bookbinding.	
1885	Automating punch cutting: Linn Boyd Benton invents the pantographic punch cutter. With this machine, an operator can trace the brass pattern of a letter with one arm of the device. A cutting tool is mounted on another arm and it engraves the letter on the punch in a reduced size. The punch cutter can be adjusted to cut a complete series of sizes from one set of patterns. Those letters have a more uniform shape than the type that previously always had to be carved manually.	
1885	Frederick and Samuel Goss found the Goss Printing Press Company in Chicago, with the financial backing of Jacob Walser. Their first product is the Clipper, a press that can print double-sided by reversing one of its cylinders. After a few difficult years the Straightline Newspaper Perfecting Press, which debuts in 1892, firmly establishes the company as a leading manufacturer of newspaper presses.	

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Year	Event	Major event
1886	Invention of the Linotype: Ottmar Mergenthaler invents the Linotype composing machine. With this typesetter, an operator can enter text using a 90-character keyboard. From a stock of letter form moulds, the machine assembles a line containing the typed text. Molten lead is then poured over this line to create a slug, a line of metal type. Once the operation is finished the matrices are returned to the type magazine from which they came. The machines are built in New York by the Mergenthaler Linotype Co. The name 'line-o'-type' is a pretty good description of what the machine does. It is widely regarded as one of the greatest advances in printing since the development of movable type 400 years earlier.	
1886	Around that same time the Swiss company Orell Gessner Füssli patents the 'Aac process' that is used to create photochroms, also called photochrome prints. In this process colourised images are produced from black and white photographic negatives via the direct photographic transfer of a negative onto a lithographic stone. Six to fifteen tint stones, each bearing an appropriate retouched image, are used to create the colour print. The photochrom technique is very popular in the 1890s and mainly used for printing postcards of city scapes.	
1889	Early pop-up books: Lothar Meggendorfer's International Circus is a pop-up book that contains six pop-up scenes of circus acts, including acrobats, clowns, and daredevil riders. Unfolded they form a circus complete with orchestra and spectators. It is not the first pop-up book to be published but thanks to reproductions, it is still available today.	
1890	First flexo press: Bibby, Baron, and Sons build the first flexographic press. This type of press uses the relief on a rubber printing plate to hold the image that needs to be printed. Because the ink that is used in that first flexo press smears easily, the device becomes known as Bibby's Folly. Later improvements in the technology do make flexography one of the most used industrial printing processes.	
1890	That same year Robert Gair accidentally invents the pre-cut cardboard box.	
1892	Eastman Kodak Company is founded: George Eastman changes the name of his company to Eastman Kodak Company, which later becomes Kodak.	
1893	Addressograph: Addressograph International starts manufacturing the Addressograph, a machine that allows business to quickly print a series of addresses on envelopes, invoices, quotes or other documents. The system uses a chain with rubber stamps that are inked and then pressed on the substrate.	
1894	First European Linotypes: De Nederlandsche Financier in Amsterdam, Holland is the first newspaper on the European continent to start using a Linotype. Two years later the Mergenthaler Setzmaschinenfabrik is founded in Berlin to cater for the European market.	

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Year	Event	Major event
1895	Harris presses: Charles and Alfred Harris found the Harris Automatic Press Company to market the first printing press with an automatic sheet feeder. The press is nearly ten times faster than handfed presses and the brothers have to understate its capabilities in order to get prospects to believe them. The company will produce many innovative presses before moving into the semiconductor business and selling off its printing division in 1983.	
1895	'Yellow Kid' by Richard Outcault is the first comic strip to use text balloons.	
1896	The Lanston Monotype Machine Company, founded by Tolbert Lanston in Washington D.C. in 1887, builds its first hot metal typesetting machine. In contrast to the Linotype which casts complete lines of type, the Monotype machine forms individual letters. That makes it easier to correct spelling mistakes by adding or removing an individual letter. This is an advantage for less time critical work, such as typesetting books. The Monotype system consists of two components: the keyboard and the composition caster. Text entered using the keyboard is output on a paper tape which can be fed into the caster which output slugs of metal type. Such a configuration allows multiple operators to typeset text that will be output on a single caster.	
1896	In 1896 Monotype issues its first typeface, Modern Condensed.	
1898	First car ad: The July issue of Scientific American includes an advertisement for the Winton Motor Carriage. This is generally considered to be the first ad for an automobile.	
1900	Kolbus starts producing bindery machines: The KOLBUS 'Rupert' is a book spine rounding and surface pressing machine that will remain in production for 55 years. It is the first in a long line of KOLBUS book bindery machines.	
1902	The first electric typewriter was produced by the Blickensderfer Manufacturing Company, of Stamford, Connecticut, in 1902.	X
1903	Offset lithography is born: Two years earlier American printer Ira Washington Rubel accidentally discovers that printing from the rubber impression roller instead of the stone plate of his lithographic press produces a clearer and sharper printed page. Based on this finding and after further refinement, the Potter Press Printing Company in New York produces the first lithographic offset press for paper.	
1906	Le Petit Larousse Illustré, a single-volume encyclopaedia, is published for the first time.	
1907	Using silk for screen printing: The Englishman Samuel Simon is awarded a patent for the process of using silk fabric as a printing screen. Screen printing quickly becomes popular for producing expensive wallpaper and printing on fabrics such as linen and silk. Screen printing had first appeared in China during the Shang Dynasty (960–1279 AD).	Label IDM1

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Year	Event	Major event
1910	By about 1910, the "manual" or "mechanical" typewriter had reached a somewhat standardised design. There were minor variations from one manufacturer to another, but most typewriters followed the concept that each key was attached to a typebar that had the corresponding letter moulded, in reverse, into its striking head. When a key was struck briskly and firmly, the typebar hit a ribbon (usually made of inked fabric), making a printed mark on the paper wrapped around a cylindrical platen. The platen was mounted on a carriage that moved left or right, automatically advancing the typing position horizontally after each character was typed. The paper, rolled around the typewriter's platen, was then advanced vertically by the "carriage return" lever (at the far left, or on the far right for left handed typewriters) into position for each new line of text. A small bell was struck a few characters before the right hand margin was reached to warn the operator to complete the word and then use the side lever to shift the paper back to the beginning of the next line.	Label IDM1
1910	The next step in the development of the electric typewriter came in 1910, when Charles and Howard Krum filed a patent for the first practical teletypewriter.	Label IDM1
1911	Roland presses: The first offset press to bear the name Roland appears on the market. It is manufactured in Offenbach, Germany by Faber & Schleicher AG. The company had been founded in 1871 and started shipping its first Albatros press 4 years later. Their 1922 single-colour Klein-Roland 00 offset press can print up to 5000 sheets per hour.	
1911	Intertype typesetters: US newspaperman Hermann Ridder founds the International Typesetting Machine Company which manufactures the Intertype. This typesetter has a simpler design than the Linotype. Late 1912 the first machine is installed at the New York Journal of Commerce. It costs $2150 which is over $50000 in today's currency.	Label IDM1
1912	Offset printing takes off: There are already 560 offset presses in operation in the United States. By the 1930s it is the dominant form of lithography.	
1914	Early graphic arts trade shows: The Bugra trade show takes place in Leipzig, Germany. Bugra stands for 'Internationale Ausstellung für Buchgewerbe und Graphik'. Around 2.3 million people visit the show which sees its visitor count reduced dramatically after the outbreak of the first World War. This is the precursor to the Drupa trade shows that take place in Dusseldorf after Leipzig becomes part of East Germany after the second World War.	
1914	In the USA demand for coil stamps is so high that Benjamin R. Stickney designs a dedicated press for stamp production. Stickney presses are manually controlled, single-colour, web-fed printing press and gumming machines. They remain in use at the Bureau of Engraving and Printing until 1957.	
1915	Hallmark, founded in 1910, creates its first Christmas card. Forty years earlier Boston printer Louis Prang had been the first to offer a line of Christmas cards in the USA.	

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Year	Event	Major event
1922	Book and type designer William Addison Dwiggins coins the term ‘graphic designer’ to describe his activities as an individual who brings structural order and visual form to printed communications. The term only achieves widespread usage after the Second World War.	
1923	KBA prints banknotes & Komori is founded: The four-colour Iris press from Koenig & Bauer can be used for printing banknotes. Over time security printing becomes one of the main focus points of the company.	
1923	Komori Machine Works is founded in Kitashinmachi, near Tokyo. Their first lithograph roll printing press is developed in 1925. A 32-inch manual sheetfed offset press follows in 1928.	
1925	Rudolf Hell invented the Hellschreiber, an early facsimile-like dot matrix-based teletypewriter device, patented in 1929	Label IDM2
1930	IBM releases Model 01 electric typewriter	Label IDM2
1932	Addressograph International merges with American Multigraph to form the Addressograph-Multigraph Corporation. For decades this company will dominate the market for addressing and duplicating machines.	
1935	First paperbacks and adhesive labels: The first commercially successful series of paperback books is published by Penguin Books in the UK. Earlier in 1931 German publisher Albatross Books had already tried to market a series of lower-priced books with a paper cover and glue binding. Penguin copied many of the concepts of their failed attempt, such as the use of colour-coded covers. The books cost sixpence each – the same price as a packet of cigarettes.	
1935	Ray Stanton Avery invents the first self-adhesive label, meant to make it easier for stores to price their products. In 1990 his company, Avery International, will merge with Dennison Manufacturing to become Avery Dennison.	
1938	Xerography is invented: Xerography, a dry photocopying technique, is invented by Chester F. Carlson. In 1947 Haloid Company, now known as Xerox, obtains a licence to commercialise the technology.	Label IDM3
1938	In 1938 the Dresden-Leipziger Schnellpressenfabrik AG changes its name to Planeta. Six years earlier the company had introduced the world’s first four-colour web offset press. After World War II Planeta becomes the largest press manufacturer of the DDR. It is acquired by Koenig & Bauer (KBA) in 1991.	
1939	Cold-glueing takes off: Emil Lumbeck is the first one to successfully use cold-glue binding for books (Lumbeck-Kaltklebebindung).	
1942	Marjory Collins photographs the production of the New York Times in order to document home front activities for the U.S. Office of War Information.	

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Year	Event	Major event
1947	Polar starts building electrically powered cutters: Polar build the Einmesser-Schnellschneider, their first electrically powered cutting machine. In 1954 they build the first cutters with an optical cutting line indicator and air cushion table.	
1948	First prototype of photocopier by Battelle and The Haloid Co.	Label IDM4
1948	Shinohara Machinery Company, the Japanese machine tool manufacturer which had been established in 1919, begins manufacturing flatbed letterpress machines.	
1949	First scans of colour images: The July issue of Fortune magazine contains the first commercial scanned colour image. It is produced using a scanner built by the Austin Company.	
1951	EAI develops analog flatbed pen plotter	X
1951	Drupa trade show: The first drupa trade show is held in Dusseldorf, Germany. Drupa, which stands for 'Druck und Paper' (print & paper), is a specialist trade fair for the printing industry.	
1952	Security printing: In Lausanne, Switzerland, Gualtiero Giori founds Organisation Giori to develop and sell technology, equipment and services for printing banknotes. This includes a centre to train state printing plant staff in the best practices in banknote design and production.	
1952-54	Fritz Karl Preikschat filed five patent applications for his teletype writer 7 stylus 35 dot matrix aka PKT printer, a dot matrix teletypewriter built between 1954 and 1956 in Germany.	Label IDM4
1954	The second drupa fair is a major success with 226388 visitors. The show highlights are engraving machines for letterpress printing. Grapha, which gets renamed to Grapha Maschinenfabrik Hans Müller A. G a year later, exhibits the BSV, its first fully automatic saddle stitcher with in-line trimmer, as well as its adhesive binder.	
1957	IBM introduces the first dot-matrix printer.	Label IDM5
1957	Transfer printing discovered.	X
1957	Dye sublimation process invented.	Label TH1
1957	First Komori four-colour press: Komori develops its first four-colour offset press, the UM-4C.	
1959	Haloid-Xerox plain-paper copier: The Xerox 914 is the first successful plain paper copier. It can make six copies per minute and had been preceded in 1949 by the 'Model A', the first commercial xerographic copier.	Labels IDM5 & IJ1 & L1 & TH1
Early 1960s	Stanford - developed technology for ink droplets using pressure wave patterns.	Label IJ2
1960s	Gerber Scientific produces plotters for printed circuit boards.	Label TH2

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Year	Event	Major event
1962	Hell HelioKlischograph: Dr. Ing. Rudolf Hell introduces the HelioKlischograph K190 – the first in a series of systems for gravure printing. Subsequent models have separate scanning and engraving units (the 1965 HelioKlischograph K193) or digital electronics (the 1974 HelioKlischograph K200). The product family still exists today.	
1962	Andy Warhol popularises screen printing, also called serigraphy, as an art form. His ‘Turquoise Marilyn’ is produced using acrylic paint and a silkscreen print on linen.	
1962	Kolbus introduce a fully automatic book finishing system that is capable of producing 36 books a minute on a continuous production line.	
1967	Océ enters the office printing market with an electro-photographic process for copying documents using a special chemically-treated type of paper. Its first plain-paper office copier follows in 1973. Instead of a xerographic process, this copier uses a developer free technology that later on will also be used in Océ’s high volume printers.	
1967	ISBN is started in Britain. The International Standard Book Number is a unique numeric identifier for commercial books.	
1967	Japanese press manufacturer Sakurai exhibits for the first time at drupa, showing off their Monarch full-automatic screen press.	
1968	The Japanese manufacturer OKI introduced its first serial impact dot matrix printer (SIDM), the OKI Wiredot. The printer supported a character generator for 128 characters with a print matrix of 7×5. It was aimed at governmental, financial, scientific and educational markets.	Label IDM6
1968	Using silicone for pad printing: Tampoprint in Germany replace the low-endurance gelatine pads used in pad printing presses by silicone pads. This allows such presses to print much longer runs on an industrial scale.	
1969	Gary Starkweather, at Xerox’s research facility in Webster, New York, demonstrates using a laser beam with the xerography process to create a laser printer.	Label L2
1969	Grapha Maschinenfabrik Hans Müller A. G and Martini merge and become Muller Martini.	
1970s	Direct thermal printer.	Label TH3
1970	Xerox plain-paper colour copier: Xerox patents expire, allowing other manufacturers such as Canon to create xerographic copiers. Xerox does, however, continue to dominate the market and launches its first plain paper colour copier, the Xerox 6500, in 1973.	Labels IDM6 & IJ3 & L2 & TH3
1970	Water-based inks are introduced.	Labels IDM6 & IJ3
1972	Presses with an integrated ink control system: The ROLAND 800 is the first sheetfed offset press with an integrated ink control system. It can print up to 10000 sheets per hour. It is one of the highlights of the drupa 1972 show.	
1973	HP 9862A plotter released for 9800 desktop calculator.	

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Year	Event	Major event
1973	All time high newspaper readership: Newspaper circulation reaches its highest level ever in the US. It will remain fairly steady until a gradual decline sets in during the mid-80s.	X
1974	The DECwriter LA36 becomes one of the first dot-matrix printers to achieve commercial success, and for a time becomes the standard dot matrix computer terminal.	Label IDM7
1974	Stored energy dot matrix printer.	Label IDM7
1974	Shinohara Machinery Company builds its first offset press, the Fuji 58.	
1974	The first Lonely Planet travel guide is published.	
1975	The first laser printers, such as the Xerox 9700, hit the market. They are prohibitively expensive but useful for applications such as cheque printing.	Label L3
1976	IBM introduces the IBM 3800 laser printer, capable of printing 20000 lines per minute.	Label L3
1976	Drop-on-demand inkjet technology developed.	Label IJ4
1977	Siemens PT-80 uses drop-on-demand inkjet technology.	
1977	Benny Landa founds Indigo, initially a research company that licences its technology to other manufacturers. This changes in the mid-80s when the company develops ElectroInk, a liquid ink that the company uses in the E-Print 1000 digital press from 1993.	
1978	Piezoelectric inkjet printer.	Label IJ5
1978	First commercially successful dot matrix printer for personal computers - Epson's TX-80.	Label IDM8
1979	Canon files the first thermal ink jet patents in Europe and the US.	Label IJ5
c. 1979	Siemens PT-80i introduced in Europe.	
1979	Canon introduces the first low-cost desktop laser printer, the Canon LBP-10.	Label L4
1979	MAN Roland Druckmaschinen AG is formed as a result of the merger of the printing press division of Maschinenfabrik Augsburg-Nürnberg and Roland Offsetmaschinenfabrik Faber & Schleicher. In 2008 the company will be renamed to Manroland.	
Late 1970s	Ballistic wire dot matrix printers.	Label IDM8
1980s & early 1990s	Dot matrix printing is the leading technology for inexpensive desktop applications.	
1980	IBM releases 5215 golf ball printer.	Label IDM8
1981	May: Xerox unveils the Star 8010 (the first laser printer designed for office use), at the National Computer Conference. Many features that were developed on the Alto are incorporated. It includes a bitmapped screen, WYSIWYG word processor, mouse, laser printer, Smalltalk language, Ethernet, and software for combining text and graphics in the same document. At a starting price of US$16-17000, the computer is not a commercial success. During its lifetime, 100000 units are produced.	
1982	Thermal wax printer.	Label TH4

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Year	Event	Major event
1982	Plastic banknotes: The American Bank Note Company prints the first plastic banknotes using DuPont's Tyvek polymers. Australia is the first country to use polymer banknotes for general circulation from 1992 onwards.	
1983	Hewlett-Packard and Canon negotiate ink-jet cross-licensing agreement.	
1984	First disposable inkjet cartridge.	Label IJ6
1984	Hewlett-Packard introduces the ThinkJet printer (thermal ink-jet).	Label IJ6
1984	The Mac is born: The Apple Macintosh is a ground-breaking computer which for the first time combines a graphical user interface and a mouse with a 'reasonable' price tag of $2490 (taking inflation into account that is over $5000 today).	Labels IJ6 & L5
1984	Adobe launches PostScript, a page description language that can be used to control output devices like laser printers. The Linotronic 300 imagesetter is the first 2400 dpi output device to ship with a PostScript RIP.	
1984	Apple Computer gives LaserWriter printer prototypes to Lotus Development, Microsoft, and Aldus, in hopes of their developing application support for it.	
1984	Hewlett-Packard introduces the LaserJet laser printer, featuring 300dpi resolution, for US$3600. This is the first laser printer intended for mass-market sales.	Label L5
1985	Desktop publishing takes off: Steve Jobs convinces John Warnock from Adobe to create a PostScript controller for their Apple LaserWriter, allowing it to output 'typesetter quality' pages. Apple and Adobe are fortunate enough that the small start-up Aldus creates an application to utilise the Mac and LaserWriter to their full extent. Aldus' software product is PageMaker.	Label L5
1985	Apple Computer commercially releases the Apple LaserWriter laser printer, using the newly released PostScript page-description language (PostScript allowed the use of text, fonts, graphics, images, and colour largely independent of the printer's brand or resolution).	
1986	Jan: Apple Computer introduces the LaserWriter Plus printer.	
1986	Hewlett-Packard introduces the QuietJet ink-jet printer.	
1986	Wapping dispute: 5500 employees of News International go on strike in a dispute over new working conditions and the proposed move from Fleet Street to new premises in the London Docklands. Despite a long and bitter battle between the strikers and the police, The Times, the Sunday Times, The Sun and the News of the World get published every single day. This Wapping dispute is a key event in the development of the British newspaper industry.	
1986	At drupa 1986 MAN Roland Druckmaschinen AG introduces its LITHOMAN commercial web offset printing press. Polar show off the POLAR Compucut, a system for computer assisted, external generation of cutting programs with automatic transfer to the cutting machine.	
1987	First colour inkjet printer - HP Paintjet.	Label IJ7

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Year	Event	Major event
1988	Hewlett-Packard introduces the DeskJet ink-jet printer (widely regarded as the 'Model T' of the industry).	Label IJ7
c. 1988	Xaar's basic patents for piezoelectric-shear print heads are filed.	Label IJ7
1990	Hewlett-Packard's introduction of the LaserJet IIP breaks the US$1000 street price barrier.	Label L6
1990	Xerox Docutech: Xerox launches its first DocuTech system, known as the DocuTech Production Publisher. The system is based on a 135 page-per-minute black & white 600 dpi xerographic print engine with attached scanner and finisher modules. It is arguably the first affordable 'print-on-demand' publishing system.	
c. 1990	Canon BJ-10e & 10v ink-jet printers introduced.	
1990-91	Peak dot matrix printer sales achieved (with seven-to-one ratio of dot matrix printers to ink-jet at this time).	Labels IDM9 & IJ8 & L6 & TH5
1991	On-press imaging: The Heidelberg GTO-DI uses Presstek plates which are imaged on the press itself. This direct imaging technology looks promising but even though other vendors start offering similar solutions it never really catches on. In 2006 Heidelberg abandons the technology.	
c. 1992	Hewlett-Packard introduces the DeskJet 1200C ink-jet printer.	
Autumn 1992	Hewlett-Packard introduces the HP LaserJet 4 laser printer.	
1993	First digital presses: The Indigo E-Print 100 is a digital press that uses ElectroInk, a kind of fluid ink which in its first incarnation can actually be rubbed off the paper. Competing systems such as the Xeikon DCP-1, introduced the same year, rely on toner. In 2002 Indigo is acquired by HP while Punch Graphix buys Xeikon.	
1993	June: Hewlett-Packard introduces the LaserJet 4ML laser printer.	
1993	QMS introduces the ColorScript Laser 1000 colour laser printer, for US$12499.	Label L7
c. 1993	Seiko Epson files critical ink-jet piezo print head patents in the US.	Label IJ9
1994	Epson introduces the MJ-700V2C (a.k.a. Stylus Color) ink-jet printer which shifted away from thermal ink-jet print heads to piezoelectric print heads. Piezoelectric print heads are better at generating multiple sized ink-jet drops, and suitable for a wider range of ink formulations. This raised the overall quality of ink-jet printers, getting close to photographic quality.	Label IJ9
1995	June: Apple Computer introduces its first colour laser printer, the Color Laser Printer 12/600PS. The 600x600 dpi printer comes with 12 MB of RAM, uses a Canon-based engine, and costs about US$7000.	
1995	At drupa MAN Roland Druckmaschinen AG launches the ROLAND 900, an innovative large format sheetfed offset press.	

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Year	Event	Major event
1995	The very first post appears on Craigslist. Within a few years, this web service has an enormous impact on US newspapers because they lose a major part of their classified ads income to the site.	
1995	Vistaprint is founded in Paris, France by Robert Keane who believes in the potential of offering short run, high-quality printing to small businesses.	
1996	April: Hewlett-Packard begins shipping the HP LaserJet 5 line of laser printers.	
c. 1996	Hewlett-Packard and Lexmark settle infringement suit with new cross-licensing agreement.	
c. 1996	Manufacturers introduce photo quality printers.	Labels IJ9 & L8
2000	Cortina waterless offset & NexPress: For press manufacturers drupa is an incredible success. Many of the big vendors, such as Heidelberg and Manroland, report an unprecedented number of sales. One of the highlights of the show is the KBA Cortina, a waterless web press for newspapers and semi-commercials. Among the digital presses the NexPress, a joint development from Heidelberg and Kodak, and the Manroland DICOweb get most of the attention. The DICOweb is, however, a short-lived commercial failure.	
2001	Market consolidation: HP acquires Indigo. Scitex sells off Vio and Karat, which is bought by KBA.	
2002	In March Belgian electronics specialist Punch buys Xeikon, which had been declared bankrupt earlier that month. The other bidders were Manroland and Yam International.	
2003	Kodak forms a dedicated commercial printing business unit. The division includes its NexPress joint venture with Heidelberg.	
2003	Decline of offset printing: The overall volume of sheetfed offset print revenues reaches its lowest point in the decade. 2007 will be the best year.	
2004	Heidelberg sells off its web press division to Goss and its NexPress digital arm to Kodak. It intends to focus uniquely on sheetfed presses.	
2005	The market for digital presses keeps expanding with the launches of the Konica Minolta Bizhub and Canon Imagepress.	
2005	EFI acquires VUTEk and enters the wide format inkjet market. It will later also acquire Jetrion, Raster Graphics, and Cretaprint, making it a dominant leader in this market.	
Mid-2000s	The emergence of cloud storage services that let you store 1000s of albums that can be accessed/retrieved on demand, as well as tablets and smartphones that put high-resolution images at users fingertips, begins to reduce demand for desktop printers.	Labels IDM10 & IJ10 & L9 & TH6
2007	Shortrun on-demand book printing: The Espresso Book Machine is a print-on-demand system that combines a printer, such as the Xerox WorkCentre 4112, with a collating, binding and cutting unit. A small colour printer is used for covers. The EBM can print a 300-page book in 4 minutes. It costs from $97000 plus printer.	

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Year	Event	Major event
2008	Printing industry is hit hard by financial crisis: A financial crisis followed by a worldwide economic downturn put a lot of pressure on the printing industry. The overall volume of print drops significantly. The newspaper industry seems to suffer the most, mainly due to higher paper prices, declining advertising revenue and increasing competition from the web.	
2008	One of the largest printing companies in the world, Quebecor World, files for Chapter 11 bankruptcy protection.	
2008	At drupa, the focus lies on inkjet printers with much attention going to high-speed, high-quality roll-fed inkjet printers from companies like HP (the T300), Screen (the Truepress Jet2500UV), Infoprint, Oce, Fujifilm (whose Jetpress 720 is the first sheetfed B2-press) and Kodak (the Stream concept press). HP introduces its latex inkjet technology, aiming to combine the ability to print durable graphics onto uncoated materials with high image quality and eco-friendliness.	
2009	Press manufacturers suffer from the crisis: The financial crisis continues. According to estimates of the American Forest & Paper Association newsprint production falls by 30% in 2009 and magazine print by 25%. Folio reports that 596 magazines disappear from the US market. One of the first cost-cutting measures that many companies take is reducing their capital expenditures. Press manufacturers suffer the most from this. According to some estimates over 30% of their deals closed at the 2008 drupa show get cancelled. Heidelberg has to apply for a 300 million Euro state loan to survive. A planned merger with Manroland is called off by the latter due to its rival's poor financial results. Oddly enough some vendors, like KBA, do not seem to suffer that much from the crisis.	
2009	Goss International installs a Goss Sunday 5000, the world's first 96-page web press, at Italian magazine printer Grafiche Mazzucchelli. Three years later Manroland will announce its solution with a web width of 2.86 metres, the 96-page LITHOMAN S.	
2009	Canon buys Océ for US $1.1bn.	
2009	Competition among printers remains fierce. A look at some typical prices shows how much these have dropped over the past years: In 1995 1000 4 colour business cards went for $125. In 2009 they cost around $9.95. In 1995 customers paid around $450 for 1000 4 colour brochures. A similar job now costs $99.	
2009	Chinese companies produce 85 million tons of paper, up from 40 million tons in 2000 and 15 million tons in 1990.	

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Year	Event	Major event
2010	At the IPEX 2010 show in Birmingham, UK the largest booths are no longer those of press manufacturers like Heidelberg or Manroland but of printer manufacturers like HP, Xerox, and Canon. Digital inkjet printing technology is the hot topic, along with web-to-print and cross-media publishing. Among the new devices that are launched are the Prosper 5000XL, Kodak's flagship colour continuous-feed press, and the Konica Minolta Bizhub C8000 digital press. Many see the success of the show as a clear indicator of the revival of the graphic arts market.	
2010	The focus on digital print is also visible at Graph Expo 2010 where Heidelberg and Komori are absent while Manroland and KBA are not showing any presses. Even though digital printing grows, it still represents only around 3% of the total print volume and 6% of the print value. According to a KBA report issued the same year, China becomes the biggest market for litho presses.	
2010	When asked what he thinks about the suggestion that the New York Times might print its last edition in 2015, its publisher Arthur Sulzberger Jr. says he sees no point in making such predictions and that all he can say is that "We will stop printing the New York Times sometime in the future, date TBD".	
2010	The World Wildlife Fund attempts to launch a 'green' file format. The WWF format is simply a PDF that cannot be printed out to 'stop unnecessary printing and encourage a new awareness about the use of paper'. The WWF initiative never gets any traction but positioning print as a sustainable industry does become a trend.	
2011	Online advertising takes over the number two spot from newspapers in the US advertising market.	
2011	Equipment manufacturers realise that their world is changing rapidly. Many of them cooperate with other vendors to try and build a presence in the digital printing market. This leads to a series of interesting partnerships: Heidelberg & Ricoh, Manroland & Océ, KBA & RR Donnelley & Son and last but not least Kodak & Konica Minolta.	
2011	Declining sales and a resulting debt of $94 million force the Japanese press manufacturer Shinohara to file for bankruptcy protection. Its sales had dropped from $60 million in March 2009 to $26 million in March 2010. In November German press manufacturer Manroland AG also files for insolvency. They state their dramatic drop in incoming orders is caused by customers having difficulty in obtaining financing for purchasing printing presses.	
2011	Xerox launches the CiPress 500 high-speed waterless inkjet press.	
2011	In its London headquarters, Stroma starts printing colour editions of international newspapers on an Océ JetStream 1000. This digital inkjet press can print in excess of 1000 36-page tabloid newspapers per hour.	

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Year	Event	Major event
2011	In the US overall sales of ebooks pass sales of paperbacks. Seven months earlier, in July 2010, web shop Amazon's US digital book sales had already eclipsed the sales of hardcover books.	
2012	Benny Landa announces a range of nanographic printing presses that combine the versatility of digital printing with the low cost and quality of offset. These presses are the buzz of the drupa show but it takes another 5 years before even the first beta site to test the technology is started.	
2012	Among the other announcements is Xeikon's Quantum toner technology. Three new B2-size sheetfed digital presses are announced: the HP Indigo 10000, Screen Truepress Jet SX & Konica Minolta KM-1. Despite the upbeat mood during the drupa show itself, attendance decreases to 314500 visitors.	
2012	Many press manufacturers change ownership: Manroland is split up. Langley Holdings purchases the sheet-fed division and the web division is acquired by Prossehl. Hans-Gronhi purchases Shinohara. Wifag buys Solna.	
2012	After 244 years the Encyclopaedia Britannica discontinues its print edition.	
2013	China Print shows the growth of the Chinese printing market: China Print, the largest Chinese graphic arts trade show, draws 180000 visitors and has almost as much floor space as drupa.	
2013	Xerox acquires Impika to extend its foothold in high-speed inkjet.	
2013	According to HP, the users of its production inkjet presses print enough pages each month to circle the earth more than 14 times.	
2013	Heidelberg announces it will phase out production of its Printmaster GTO 52 from March 2014. Since its launch in 1972 106000 units have been sold worldwide. The press manufacturer intends to focus sales on its Speedmaster SM 52 and SX 52 devices and its Linoprint C 901 and C 751 digital printers.	
2014	Vistaprint acquires the Dutch Drukwerkdeal.nl as well as a 97% stake in Italian web-to-print business Pixartprinting and a $25 million stake in Brazilian web-printing start-up Printi.	
2014	French press manufacturer MGI uses the British Ipex trade show as the global launchpad its new Meteor DP8700 XL+ digital press, DF Pro inline finishing unit, and JETvarnish digital spot coater. The Ipex show itself is smaller than previous editions because Heidelberg, Agfa and several digital press vendors decide to no longer attend it.	
2014	Xerox launches the Versant 1200 digital press, to compete with the Konica Minolta C8000 and Ricoh C901 in the mid-range segment of the digital printing market.	
2014	Heidelberg stops manufacturing saddlestitchers and perfect binders but it continues its line of Stahlfolder folding machines.	
2014	In the USA print keeps getting less attention from the average consumer. Packaging, sign & display and other markets are as healthy as ever.	

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Year	Event	Major event
2014	At Graph Expo 2014 in Chicago, one of the show highlights are the digital die-cutting devices of Highcon, an Israeli company.	
2015	At the Labelexpo Europe trade show Gallus showcases the first modular digital inline label printing system, the DCS 340, which is later relabelled as the Labelfire 340.	
2015	Müller Martini stops making printing presses and shifts its focus entirely to finishing machines.	
2015	Flint Group acquires Xeikon and uses the press and consumables manufacturer as the basis of a new digital division, Flint Group Digital Printing Solutions.	
2016	At the drupa trade show digital printing in general and specifically inkjet printing on corrugated packaging board attracts a lot of attention. Among the presses shown or previewed are the EFI Nozomi C18000, the HP PageWide C500, and the Durst Rho 130 SPC.	
2016	Several vendors showed digital embellishing and finishing equipment. A prime example is the Scodix E106 which can be used, among others, to add foils to short or medium run folding cartons.	
2016	Bertelsmann creates the Bertelsman Printing Group, Europe's biggest printing group with revenues of EU1.7 billion and nearly 9000 employees.	

Table A11: Timeline of solar technologies [Shahan, 2012, EIA, 2008c,a,b, Randall, 2017]

Year	Event	Major event
1767	The Solar Oven: Swiss physicist, alpine explorer, and aristocrat Horace de Saussure is credited with inventing the first working solar oven, amongst other discoveries. Constructed from 5 layers of glass and measuring around 12 inches across, the oven worked by allowing light to pass through the glass before being absorbed by the black lining and turned into heat. The heat is then reflected by the glass, therefore heating the space inside the box up to 87.5 degrees Celsius. He wrote that "Fruits... exposed to this heat were cooked and became juicy."	X
1839	The Photovoltaic Effect: Edmond Bequerel, born in Paris in 1820, discovered that when two electrodes were placed in an electrolyte (electricity-conducting solution), a voltage developed when light fell upon the electrolyte. This provided the basic principles for solar power.	X
1860	Auguste Mouchout (France), a mathematics instructor, was able to convert solar radiation directly into mechanical power.	Label TH1
1873	Selenium: An English Electrical engineer, Willoughby Smith, discovered the photoconductivity of selenium entirely by accident. He was developing a method for continually testing underwater telegraph cables as they were being laid and chose selenium rods as a semi-conductor with high resistance for his test circuit. Although selenium appeared to be up to the job, inconsistent results kept occurring. Smith realised that the conductivity of selenium was affected by the amount of light it was exposed to. He described the effect in a paper published in Nature in February of that year.	X
1876	Electricity from Light: A King's College Professor, William Grylls Adams, and his student, Richard Evans Day, found in 1876 that solidified selenium produced electricity when exposed to light. They attached platinum electrodes to selenium and observed a current in the electrodes when the selenium was exposed to light. Although there was not enough electricity to power anything, they had shown that electricity could be generated from light without the use of any moving parts. They published a paper on the selenium cell: "The action of light on selenium", in Proceedings of the Royal Society, A25, 113 in 1877.	X
1878	Augustin Mouchot displays a solar power generator at the Universal Exhibition in Paris.	X
1878	William Adams (England) constructed a reflector of flat-silvered mirrors arranged in a semicircle. To track the sun's movement, the entire rack was rolled around a semicircular track, projecting the concentrated radiation onto a stationary boiler.	Label TH2
1883	The First Working Solar Cell: American inventor Charles Fritts developed the first solar cell, applying selenium to a thin layer of gold. This method was only able to achieve 1 to 2% efficiency, making it impractical for general use.	X
1883-84	John Ericsson (United States) invented and erected a solar engine that used parabolic trough construction.	Label TH3

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Year	Event	Major event
1887	Heinrich Hertz investigates ultraviolet light photoconductivity and discovers the photoelectric effect	X
1887	James Moser reports dye sensitised photoelectrochemical cell.	
1888	Edward Weston receives patents US389124 and US389125 for a “Solar cell”.	X
1888-91	Aleksandr Stoletov creates the first solar cell based on the outer photoelectric effect	X
1894	Melvin Severy receives patents US527377 and US527379 for his “Solar cell”.	
1897	Harry Reagan receives patent US588177 for his “Solar cell”.	
1901	Philipp von Lenard observes the variation in electron energy with light frequency.	
1904	Wilhelm Hallwachs (German) discovered that a combination of copper and cuprous oxide was sensitive to light.	Label PV1
1905	Einstein’s Paper on Light & Electrons: In the paper “On a Heuristic Viewpoint Concerning the Production and Transformation of Light” Einstein set out for the first time the photoelectric relationship between light and electrons on a quantum basis. Although controversial at the time, it was gradually accepted by the scientific community and led to his winning of the Nobel Prize in 1921.	Label PV1
1913	William Coblentz receives patent US1077219 related to his “Solar cell”.	
1914	Sven Ason Berglund patents “methods of increasing the capacity of photosensitive cells”.	
1916	Robert Millikan experimentally proves Einstein’s theory of the photoelectric effect.	
1918	Accidental Crystals: Jan Czochralski, a polish scientist, discovers a method for creating single-crystal silicon entirely by accident — he mistakenly dipped his pen in a crucible of molten tin rather than an inkwell. The result was a thin thread of solidified metal. Single-crystal semi-conductors and metals became important throughout electronics — their efficiency and stability not only contributing to the development of silicon solar cells, but also crucial to the creation of transistors for microprocessor units.	Label PV2
1920s	Solar water-heating systems, utilising “flat collectors” (or “flat-plate collectors”), relied upon in homes and apartment buildings in Florida and southern California.	Label TH4
1921	Albert Einstein wins the 1921 Nobel Prize in Physics for his theories that explained the photoelectric effect.	X
1932	Audobert and Stora discover the photovoltaic effect in Cadmium selenide (CdSe), a photovoltaic material still used today.	Label PV3
1935	Anthony H. Lamb receives patent US2000642 for his “Photoelectric device”.	
1941	Russell Ohl files patent US2402662 for a “Light sensitive device”.	
1947	Energy was scarce during World War II so passive solar buildings became popular in the United States.	
1947	Libbey-Owens-Ford Glass Company published a book titled, Your Solar House, which profiled 49 of the nation’s greatest solar architects.	

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Year	Event	Major event
1948	Gordon Teal and John Little adapt the Czochralski method of crystal growth to produce single-crystalline germanium and, later, silicon.	Label PV4
1950s & 60s	The Space Race: The burgeoning space industry's need for a sustainable power source in the earliest satellites led to investment and development in solar technology. Satellites such as Explorer VI and VII and the first telecommunications satellite Telstar 1 (launched by Bell Labs) utilised the most cutting edge (at the time) solar cells, achieving up to 14 watts from their photovoltaic arrays.	
1953	Gerald Pearson begins research into lithium-silicon photovoltaic cells.	
1954	A Major Breakthrough: Three researchers at Bell Labs — Daryl Chapin, Calvin Fuller, and Gerald Pearson — invent the first practical silicon solar cells, announced by Bell Labs on the 25th of April. Chapin had for several years been experimenting with selenium-based solar cells but was unable to achieve an efficiency above 1% (for comparison, internal combustion achieves around 20%). At the same time, Fuller and Pearson were developing silicon transistors and found that one of these, when exposed to light, generated electricity. The three scientists joined forces and in 1954 presented their 'solar battery', powering a small toy windmill and a radio, at an efficiency of 6%. The key to this was their ability to diffuse boron into silicon, a process known as doping. The New York Times forecasts that solar cells will eventually lead to a source of "limitless energy of the sun". This first solar cell was the size of a small coin, and although not commercially viable, is the basis for solar cell development ever since.	Label PV5
1955	Western Electric began to sell commercial licences for silicon photovoltaic technologies. Hoffman Electronics-Semiconductor Division creates a 2% efficient commercial solar cell for $25/cell or $1785/watt. Early successful products included PV-powered dollar bill changers and devices that decoded computer punch cards and tape.	
1956	In the mid-50s, engineer Don Paxton and architect Frank Bridgers designed the world's first commercial solar building at 213 Truman N.E., Albuquerque, NM. Utilising a south-facing glass wall tilted to 30 degrees, alongside mechanical and "passive" solar technologies, the structure was well ahead of its time. Relying on mechanical solutions where computer control would nowadays be used, they achieved a remarkable level of efficiency through solar heating and thermal storage. The template that they created is still utilised in creating energy-efficient homes and commercial premises today.	Label TH5
1957	AT&T assignors (Gerald L. Pearson, Daryl M. Chapin, and Calvin S. Fuller) receive patent US2780765, "Solar Energy Converting Apparatus". They refer to it as the "solar battery". Hoffman Electronics creates an 8% efficient solar cell.	Label PV6

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Year	Event	Major event
1958	T. Mandelkorn, U.S. Signal Corps Laboratories, creates n-on-p silicon solar cells, which are more resistant to radiation damage and are better suited for space. Hoffman Electronics creates 9% efficient solar cells. Vanguard I, the first solar powered satellite, was launched with a 0.1W, 100 cm^2 solar panel.	Label PV6
Late 1950s	Increasing Efficiency: Throughout the late 50s, Hoffman electronics developed increasingly more efficient solar cells. It started out initially at an 8%-efficient cell in 1957, before eventually increasing to a 14%-efficient, commercially available cell in 1960.	Label PV6
1961	"Solar Energy in the Developing World" conference is held by the United Nations.	X
1962	The Telstar communications satellite is powered by solar cells.	Label PV7
1963	Sharp Corporation produces a viable photovoltaic module of silicon solar cells.	
1964	Farrington Daniels' landmark book, Direct Use of the Sun's Energy, published by Yale University Press.	
1967	Soyuz 1 is the first manned spacecraft to be powered by solar cells	
1967	Akira Fujishima discovers the Honda-Fujishima effect which is used for hydrolysis in the photoelectrochemical cell.	X
1968	Roger Riehl introduces the first solar powered wristwatch.	
1969	A "solar furnace" was constructed in Odeillo, France; it featured an eight-story parabolic mirror.	Label TH6
1970s	Commercial Viability: Despite the great advances over twenty years or so, solar technology was still too expensive to be commercially viable in terrestrial installations. In the early 70s, Dr. Elliot Berman (with funding from Exxon Corp.) designed a much lower cost solar cell, using lower-grade silicon and cheaper housings which brought the cost per watt down from $100 to just $20. Installations far from mains electricity (i.e. oil rigs) used the cells over expensive and cumbersome batteries, giving terrestrial solar technology the capital boost it needed to become a viable mainstream solution.	X
1970	First highly effective GaAs heterostructure solar cells are created by Zhores Alferov and his team in the USSR.	
1971	Salyut 1 is powered by solar cells.	
1972	The Institute of Energy Conversion: The first laboratory dedicated to the development of PV research is established at the University of Delaware.	Label PV8
1973	Skylab is powered by solar cells.	
1973	The University of Delaware builds "Solar One", a PV/thermal hybrid system, and the world's first PV-powered houses. Roof-integrated arrays fed surplus power through a special meter to the utility during the day; power was purchased from the utility at night (the model known today as the solar 'feed-in'). In addition to providing electricity, the arrays were like flat-plate thermal collectors; fans blew warm air from over the array to heat storage bins.	Labels PV8 & TH7

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Year	Event	Major event
1973	The Arab Oil Embargo occurred, in which several Arab nations in the Organization of Petroleum Exporting Countries (OPEC) embargoed oil to the United States and Holland to protest their support of Israel in the Arab-Israeli "Yom Kippur" War. Arab OPEC production was cut by 25%, which caused some temporary shortages and helped oil prices to triple. This contributed to an increased interest in alternatives to petroleum, including nuclear power.	Label TH7
1973	Spurred by the oil embargo, interest in space applications of photovoltaics grows.	Label PV8
1974	Florida Solar Energy Center begins.	
1974	J. Baldwin, at Integrated Living Systems, co-develops the world's first building (in New Mexico) heated and otherwise powered by solar and wind power exclusively.	
1974	The Solar Energy Industries Association (SEIA) was formed. The organization represents the interests of the solar industry and acts as a lobbying group in Washington, DC.	Labels PV8 & TH7
1976	David Carlson and Christopher Wronski of RCA Laboratories create first amorphous silicon PV cells, which have an efficiency of 1.1%.	
1977	Global Photovoltaic manufacturing production exceeds 500 kilowatts for the first time	
1977	The Solar Energy Research Institute (SERI) was formed in the U.S. (now the National Renewable Energy Laboratory [NREL]), a national laboratory that provides research and development support for solar and photovoltaic technologies.	Labels PV9 & TH7
1978	First solar-powered calculators.	
1978	First Feed-In Tariff Implemented: The first form of feed-in tariff was implemented in the U.S. in 1978 under President Jimmy Carter, after signing the National Energy Act (NEA). Its purpose was to encourage energy conservation and the development of new energy resources, including renewables such as solar, wind, and geothermal power.	
1978	The Public Utility Regulatory Policies Act (PURPA) of 1978 mandated the purchase of electricity from qualifying facilities that meet certain standards on energy source and efficiency.	Labels PV9 & TH7
1978	The Energy Tax Act of 1978 established a 10-percent investment tax credit for photovoltaic applications.	Labels PV9 & TH7
1978	A 15% energy tax credit was added to an existing 10% investment tax credit, providing incentive for capital investment in solar thermal generation facilities for independent power producers.	X
1978	The Solar Photovoltaic Energy, Research, Development and Demonstration Act of 1978 committed $1.2 billion, over 10 years, to improve photovoltaic production levels, reduce costs, and stimulate private sector purchases.	Label PV9
1978	Photovoltaic energy commercialisation program accelerated the procurement and installation of photovoltaic systems in U.S. Federal facilities.	

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Table A11 – continued from previous page

Year	Event	Major event
1979	President Jimmy Carter Installs 1st White House Solar Panels.	
Late 1970s	By the late 1970s, a program for the development of distributed photovoltaics was established by the U.S. Government at the Massachusetts Institute of Technology, focusing on design and demonstration issues for the buildings sector.	
1980s	Solar Hits the Mainstream: Throughout the 1980s, solar developments continued at apace. Thin-film solar cells allowed for smaller, cheaper, and more-efficient solar installations, on buildings, vehicles, and consumer items (such as hand-held calculators).	
1980	John Perlin and Ken Butti's landmark book A Golden Thread published, covering 2500 Years of Solar Technology from the Greeks and Romans until the modern day	
1980	The Carlisle house (Massachusetts) was completed with participation from MIT, the U.S. DOE, and Solar Design Associates. It featured the first building-integrated photovoltaic system, passive solar heating and cooling, superinsulation, internal thermal mass, earth-sheltering, daylighting, a roof-integrated solar thermal system, and a 7.5-peak-watt photovoltaic array of polycrystalline modules from Solarex.	
1980	The Crude Oil Windfall Profit Tax Act of 1980 was enacted, raising the residential tax credit to 40% of the first $10000 for photovoltaic applications, and the business tax credit to 15%. The Act also extended the credit to the end of 1981.	Label PV10
1980	Boeing, Kodak, and the Institute of Energy Conversion at University of Delaware fabricated the first thin-film photovoltaic cells with efficiencies greater than 10% using Cu_2S/CdS technology.	Label PV10
1981	President Ronald Reagan orders solar panels on the White House to be removed.	
1981	California enacted a 25% tax credit for the capital costs of renewable energy systems.	Labels PV10 & TH8
1982	Kyocera Corp is the first manufacturer in the world to mass-produce Polysilicon solar cells using the casting method, today's industry standard.	
1982	Solar-Powered Vehicles: German automobile manufacturer Volkswagen start testing solar PV arrays on the tops of Dasher station wagons. An array generate approximately 160 watts for the vehicle's ignition system.	
1982	Solar One (solar tower, not to be confused with previous PV house), a 10-megawatt central receiver demonstration project, was first operated and established the feasibility of power tower systems. In 1988, the final year of operation, the system achieved an availability of 96%.	Label TH8
1983	Worldwide photovoltaic production exceeds 21.3 megawatts, and sales exceed $250 million.	
1983	California's Standard Offer Contract system provided renewable electric energy systems with a relatively firm, stable market for their output. This system allowed the financing of capital-intensive technologies such as solar thermal-electric.	Label TH8

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Table A11 – continued from previous page

Year	Event	Major event
1983	The SEGS I plant (13.8-megawatt) was installed, the first in a series of Solar Electric Generating Stations (SEGS). SEGS I used solar trough technology to produce steam in a conventional steam turbine generator. Natural gas was used as a supplementary fuel for up to 25% of the heat input.	Label TH8
1984	30000 ft^2 Building-Integrated Photovoltaic [BI-PV] Roof completed for the Intercultural Center of Georgetown University. Eileen M. Smith, M.Arch. took 20th Anniversary Journey by Horseback for Peace and Photovoltaics in 2004 from solar roof to Ground Zero NY World Trade Center to educate public about BI-PV Solar Architecture. Array was still generating an average of one MWh daily as it has since 1984 in the dense urban environment of Washington, DC.	
1984	Advanco and McDonnell Douglas systems demonstrated the potential for the high-efficiency 25-kilowatt solar dish.	Label TH8
1984	Dish/engine systems convert the thermal energy in solar radiation to mechanical energy and then to electrical energy — in much the same way that conventional power plants convert thermal energy from combustion of a fossil fuel to electricity.	
1984	The Sacramento Municipal Utility District commissioned its first 1-megawatt photovoltaic electricity-generating facility.	X
1985	20% efficient silicon cells are created by the Centre for Photovoltaic Engineering at the University of New South Wales.	X
1985	The 6-megawatt Carissa Plains plant was added to Southern California Edison's system. The project was later dismantled.	
1986	'Solar-Voltaic Dome™' patented by Lt. Colonel Richard T. Headrick of Irvine, CA as an efficient architectural configuration for building-integrated photovoltaics.	
1986	Kramer Junction: World's largest solar thermal facility scheduled to be built in Kramer Junction, California. The facility consisted of rows of mirrors that concentrated energy from the sun into a system of pipes that circulated a heat transfer fluid. This fluid was then used to produce steam, which would power a conventional turbine with which to generate electricity.	Label TH8
1988	The Dye-sensitised solar cell is created by Michael Grätzel and Brian O'Regan (chemist). These photoelectrochemical cells work from an organic dye compound inside the cell and cost half as much as silicon solar cells.	Label PV11
1988-91	AMOCO/Enron used Solarex patents to sue ARCO Solar out of business.	
1989	Reflective solar concentrators are first used with solar cells.	Label TH9
1989	Federal regulations that govern the size of solar power plants were modified to increase maximum plant size to 80 megawatts from 30 megawatts.	Label TH9

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Table A11 – continued from previous page

Year	Event	Major event
1989	The U.S. Renewable Energy and Energy Efficiency Technology Competitiveness Act of 1989 sought to improve the operational reliability of photovoltaic modules, increase module efficiencies, decrease direct manufacturing costs, and improve electric power production costs.	
1989	PV for Utility Scale Applications (PVUSA), a U.S. national public-private partnership program, was created to assess and demonstrate the viability of utility-scale photovoltaic electric generating systems. PVUSA participants include the DOE and other agencies, the Electric Power Research Institute, the California Energy Commission, and Pacific Gas & Electric (PG&E) and eight other utilities.	
1990	The Magdeburg Cathedral installs solar cells on the roof, marking the first installation on a church in East Germany.	
1990	Start of the 1000 Roof Program in Germany, Accompanied by the National Power Feed-in Law: As in the case of the Carter feed-in tariff scheme, the tariffs were below end-consumer prices, with the high cost of PV at that time, and it did much for PV development.	Label PV11
1990	Siemens A.G. of Munich, West Germany, acquired California-based ARCO Solar, the world's largest photovoltaic company.	
1990	The PV Manufacturing Technology (PVMaT) project began. A government-industry research and development partnership between DOE and members of the U.S. photovoltaic industry was designed to improve manufacturing processes, accelerate manufacturing cost reductions for photovoltaic modules, improve commercial product performance, and lay the groundwork for a substantial scale-up of manufacturing capacity.	
1991	Efficient Photoelectrochemical cells are developed	Label PV11
1991	President George H. W. Bush directs the U.S. Department of Energy to establish the National Renewable Energy Laboratory (transferring the existing Solar Energy Research Institute).	
1991	Luz International went bankrupt while building its tenth SEGS plant. SEGS I through IX remained in operation.	
1992	A 7.5-kilowatt dish prototype system became operational, using an advanced stretched-membrane concentrator, through a joint venture of Sandia National Laboratories and Cummins Power Generation.	
1992	The Energy Policy Act of 1992 restored the 10% investment tax credit for independent power producers, using solar technologies.	Labels PV11 & TH9
1992	The University of South Florida fabricated a 15.89% efficient thin-film cell, breaking the 15% barrier for the first time	Label PV11
1993	The National Renewable Energy Laboratory's Solar Energy Research Facility is established.	

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Table A11 – continued from previous page

Year	Event	Major event
1993	Pacific Gas and Electric completed the installation of the first grid-supported photovoltaic system in Kerman, California. The 500-kilowatt system was the first effort aimed at "distributed power", whereby a relatively small amount of power is carefully matched to a specific load and is produced near the point of consumption.	
1993	New world-record efficiencies in polycrystalline thin film and in single-crystal devices, approaching 16% and 30%, respectively, were achieved in 1993.	
1994	The first solar dish generator, using a free-piston Stirling engine, was tied to a utility grid.	Label TH9
1994	The Corporation for Solar Technology and Renewable Resources, a public corporation, was established to facilitate solar developments at the Nevada Test Site.	
1994	3M Company introduced a new silvered plastic film for solar applications.	
1994	The National Renewable Energy Laboratory (NREL) developed a solar cell made of gallium indium phosphide and gallium arsenide; it was the first one of its kind to exceed 30% conversion efficiency.	
1995	Federal Energy Regulatory Commission (FERC) prohibits qualifying facility contracts above avoided costs.	
1995	An Amoco-Enron joint venture announced its intention to use amorphous silicon modules for utility-scale photovoltaic applications.	
1996	The U.S. National Center for Photovoltaics is established. Graetzel, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland achieves 11% efficient energy conversion with dye-sensitised cells that use a photoelectrochemical effect.	
1996	Flight of the Icare: The Icare, which at the time was the world's most advanced solar-powered plane, flew over Germany in 1996. Over 3000 super-efficient solar cells covered the wings and tail surfaces of the plane.	Label PV12
1996	Development began on Solar Two, an upgrade of its 1973 Solar One (PV-hybrid houses, not to be confused with later solar tower project of the same name) project. Solar Two was a huge advancement in that it demonstrated the ability to produce power even when the sun is not shining. This also helped foster commercial interest in power towers.	Label PV12
1998	Subhendu Guha, a scientist noted for his pioneer work in amorphous silicon, led the invention of flexible solar shingles, a roofing material and state-of-the-art technology for converting sunlight into electricity on buildings.	
1999	Total worldwide installed photovoltaic power reaches 1000 megawatts.	
1999	Researchers at the NREL developed a record-breaking prototype solar cell that measured 18.8% efficiency, topping the previous record for thin-film cells by more than 1%.	
1999	32.3% Efficiency: Spectrolab, Inc. worked with the National Renewable Energy Laboratory to develop a photovoltaic solar cell that converted 32.3 percent of received sunlight into electricity by combining three layers of photovoltaic materials into a single cell.	Label PV13

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Table A11 – continued from previous page

Year	Event	Major event
1999	A “100000 Solar Roofs” program was started in Germany with the goal of creating a PV power capacity of 300 MW within six years. The program was initiated by Dr. Hermann Scheer, member of the German Parliament and president of EUROSOLAR.	Label PV13
1999	Construction was completed on Four Times Square in New York, New York. The office building had more energy-efficient features than any other commercial skyscraper and included building-integrated photovoltaic panels on the 37th to 43rd floors, on the south- and west-facing facades, to produce part of electricity needed for the building.	
2000	Hermann Scheer Introduces the National Renewable Energy Act in German Parliament: Its unique property was the introduction of technology-dependent feed-in tariffs. For PV, the tariff levels were way above end-consumer prices. This created an (artificial) market that allowed the PV industry to grow from a niche player to a mature industry. The second unique part is the continuous reduction in the tariffs baked into the law that forces the industry to stay on its toes.	Label PV13
2000	A 12-kilowatt solar electric system, in Colorado, was the largest residential installation in the United States to be registered with the U.S. Department of Energy’s Million Solar Roofs Initiative. The system provided most of the electricity for the family of eight’s 6000-square-foot home.	
2000	First Solar began production at the Perrysburg, Ohio, photovoltaic manufacturing plant. Each year, it could produce enough solar panels to generate 100 megawatts of power.	
2000	Astronauts began installing solar panels at the International Space Station, on the largest solar power array deployed in space. Each “wing” of the array consisted of 32800 solar cells.	
2001	Home Depot began selling residential solar power systems in three stores in San Diego, California.	
2001	NASA’s solar-powered aircraft, Helios, set a new world altitude record for non-rocket-powered craft: 96863 feet (more than 18 miles).	
2001	BP and BP Solar announced the first BP Connect gasoline retail and convenience store in the United States. The Indianapolis, Indiana, service station features a solar-electric canopy. The canopy contains translucent photovoltaic modules made of thin-film silicon integrated into glass.	
2002	Students from the University of Colorado built an energy-efficient solar home for the Solar Decathlon, a competition sponsored by the Department of Energy. Student teams integrated aesthetics and modern conveniences with maximum energy production and optimal efficiency. The houses were transported to the National Mall in Washington, DC, where the student team took first prize overall.	
2003	George Bush has a 9 kW PV system and a solar thermal systems installed on grounds keeping building at the White House	

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Year	Event	Major event
2004	Kansas Governor Kathleen Sebelius issued a mandate for 1000 MW renewable electricity in Kansas by 2015 per Executive Order 04-05.	Label PV14
2004	1 GW of PV installed in Germany	X
2004	One Million Solar Roofs: California Governor Arnold Schwarzenegger proposes Solar Roofs Initiative for one million solar roofs in California by 2017.	Label PV14
2006	California Public Utilities Commission approved the California Solar Initiative (CSI), a comprehensive $2.8 billion program that provides incentives toward solar development over 11 years.	Labels PV14 & TH10
2006	Polysilicon use in photovoltaics exceeds all other polysilicon use for the first time: contributing to this is the lower cost of manufacture than monocrystalline counterparts.	
2006	New world record achieved in solar cell technology when a new solar cell breaks the “40 Percent Efficient” sunlight-to-electricity barrier.	Label PV14
2007	Construction of Nellis Solar Power Plant, a 15 MW PPA installation.	X
2007	The Vatican announced that in order to conserve Earth’s resources they would be installing solar panels on some buildings, in “a comprehensive energy project that will pay for itself in a few years”.	
2007	Google solar panel project begins operation.	
2007	Nanosolar ships the first commercial printed CIGS, claiming that they will eventually ship for less than $1/watt. However, the company does not publicly disclose the technical specifications or current selling price of the modules.	
2007	Boeing Spectrolab and the NREL created the High-Efficiency Metamorphic Multijunction Concentrator Solar Cell, or HEMM solar cell, which achieved the highest efficiency level of any photovoltaic device to date. The HEMM solar cell broke the 40% conversion efficiency barrier, making it twice as efficient as a typical silicon cell. However, it was only under the concentrated energy of 326 suns that this was achieved. The inverted metamorphic triple-junction solar cell was designed, fabricated and independently measured at NREL.	X
2007	42.8% Efficiency: University of Delaware claims to achieve new world record of 42.8% in solar cell technology without independent confirmation.	X
2007	The Technische Universität Darmstadt won the 2007 Solar Decathlon. The team won the architecture, lighting, and engineering contests.	
2010	US President Barack Obama orders installation of additional solar panels and a solar water heater at the White House	
2011	Fast-growing factories in China push manufacturing costs down to about $1.25 per watt for silicon photovoltaic modules. Installations double worldwide.	Label PV15
2012	3D PV-cell with 30% more energy efficiency	
2013	After three years, the solar panels ordered by President Barack Obama were installed on the White House.	

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Year	Event	Major event
2016	University of New South Wales engineers established a new world record for unfocused sunlight conversion to electricity with an efficiency increase to 34.5%. The record was set by UNSW's Australian Centre for Advanced Photovoltaics (ACAP) using a 28 cm² four-junction mini-module – embedded in a prism – that extracts the maximum energy from sunlight. It does this by splitting the incoming rays into four bands, using a four-junction receiver to squeeze even more electricity from each beam of sunlight.	X
2016	First Solar says it has converted 22.1 percent of the energy in sunlight into electricity using experimental cells made from cadmium telluride—a technology that today represents around 5 percent of the worldwide solar power market.	
2017	2nd August: Tesla completes its first solar roof installations for company employees and opens up pre-orders	Label PV16

Table A12: Timeline of tide, wave, and ocean electricity [Tester et al., 2012]

Year	Event	Major event
BC-AD	References to use of tides in classical Greece, possibly dating back to the time of Aristotle	
960 AD	Reference to tide mills at Basra in southern Iraq	
1041 & 1078	First references to European tide mills (around Venice)	X
1100-1900	Waterwheel-driven mills powered by tidal impoundments and currents operational in England, western Europe, and colonial Boston, among other places	
1135-WWII	Bromley-by-Bow Tidal Mill near London	
1734	Slade's Tidal Spice Mill, Chelsea, Massachusetts	
1799	Girard files first patent on wave-energy device in France	X
1800-1900	25 tide mills cited in Britain	
1871	Jules Verne's fictional Captain Nemo posits thermoelectricity from ocean water in the novel 20,000 Leagues under the Sea	Label 1
1881	D'Arsonval proposes concept of ocean thermal energy conversion (OTEC)	Label 2
1892	Stahl notes 19 wave-power concepts in American Society of Mechanical Engineers (ASME) transactions	
1910	Bochaux-Praceique lights and powers his house at Royan, near Bordeaux in France, using wave power - first oscillating water-column type of wave-energy device	Label 3
1934	Claude tests open-cycle OTEC in Cuba	Label 4
1935-77	Succession of studies of Passamaquoddy/Bay of Fundy tidal power stations	Label 4
1940s	Pioneering of modern scientific pursuits in wave energy by Yoshio Masuda's experiments in the 1940s	Label 5
1950s	Yoshio Masuda's concept for extracting power from the angular motion at the joints of an articulated raft	Label 6
1959	First of a number of small (i.e. less than 1 MWe) tidal power plants reported in China	Label 7
1966	Rance River tidal power plant operational in France	Label 8
1969	Experimental tidal unit constructed in Kislaya Guba, Russia	X
1972-84	US OTEC program	Label 9
1973	Renewed interest in wave energy was motivated by the oil crisis in 1973	Label 9
1974	Stephen Salter's 'nodding duck' is invented (a.k.a. Edinburgh Duck). In small scale controlled tests, the Duck's curved cam-like body can stop 90% of wave motion and can convert 90% of that to electricity giving 81% efficiency.	Label 9
1976-82	British launch, then suspend, their wave-power program; revised post-2000	Label 9
1977	Wells invents turbine which rotates in same direction when airflow is reversed	Label 9
1978	Japanese install 125 kWe wave-power unit off Honshu	Label 9

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Year	Event	Major event
1979	Mini-OTEC operated in Hawaii by the US and by Japanese off Shimane	Label 9
1984	20 MW Annapolis tidal station operational in Nova Scotia	Label 10
1985	KVAERNER wave-energy converter deployed in Norway; later succumbs to storm	
1986-2000	Decline, on the average, of fossil energy prices in constant dollars saps motivation for vigorous pursuit of the more expensive categories of alternatives, e.g., anything out at sea. This is then reinvigorated by post-2000 oil price escalation	Label 11
1995	2 MWe OSPREY wave-power station wrecked during installation	
2003	European Marine Energy Centre established in the Orkney Islands off northern Scotland (world's first marine energy test facility)	Label 12
2007	Pelamis devices operational at first commercial wave-power stations off Orkney and Portugal, where more are planned	Label 13
2007	Underwater tidal stream turbines installed in New York City's East River	Label 13
2008	Scottish government offers $20 million Saltaire Prize for best demonstrated innovation in wave or tidal power	Label 13
2009	Wave Hub project off Cornish coast in England; scheduled to test multiple concepts	

Table A13: Timeline of turbojets [Boyne et al., 1979, GE Aircraft Engines (Firm), 1990, Gunston, 1998, Jr, 1999, Fafard, 2015, Roberts, 2004]

Year	Event	Major event
Prehistoric times	Ordovician period: the first known cephalopods: they swim by a natural built-in reciprocating hydrojet.	
120-150 BC	Hero of Alexandria demonstrates the principles of jet reactions in the Aeolipile (a steam jet/rocket engine on a bearing).	X
1232	The Chinese begin to use rockets as weapons.	
1500	Leonardo da Vinci sketched a contraption, the chimney jack, that rotated due to the effects of hot gases flowing up a chimney.	
1629	Giovanni Branca develops a stamping mill that utilised jets of steam to operate the machinery.	
1687	Sir Isaac Newton presents his three laws of motion. These form the basis for modern propulsion theory.	X
1791	John Barber applies and receives the first patent for a simple turbine machine. This is British patent #1833 for 'A Method for Rising Inflammable Air for the Purposes of Producing Motion and Facilitating Metallurgical Operations'. In it he describes a turbine.	X
1872	First true gas turbine engine designed by Dr. F. Stolze.	
1884	Charles Algernon Parsons patents the steam turbine. In the patent application he notes that the turbine could be driven "in reverse" to act as a compressor. He suggests using a compressor to feed air into a furnace, and a turbine to extract power to run the compressor. Although intended for factory use, he is clearly describing the gas turbine.	X
1887	Gustaf de Laval introduces nozzles design of small steam turbines.	
1897	Steam turbine used to power a ship for the first time.	
1900	Sanford Alexander Moss publishes a paper on turbocompressors. He builds and runs a testbed example in 1903.	Label 1
1903	Ægidius Elling builds a gas turbine using a centrifugal compressor which runs under its own power. By most definitions, this is the first working gas turbine.	Label 2
1903-06	The team of Armengaud and Lemale in France build a complete gas turbine engine. It uses three separate compressors driven by a single turbine. Limits on the turbine temperatures allow for only a 3:1 compression ratio, and the turbine is not based on a Parsons-like "fan", but a Pelton wheel-like arrangement. The engine is so inefficient, at about 3% thermal efficiency, that the work is abandoned.	
1908	Hans Holzwarth starts work on extensive research on an "explosive cycle" gas turbine, based on the Otto cycle. This design burns fuel at a constant volume and is somewhat more efficient. By 1927, when the work ended, he has reached about 13% thermal efficiency.	
1908	René Lorin patents a design for the ramjet engine.	X
1909	Marconnt proposes a modification of Lorin's design using a resonant compression chamber, creating the pulsejet.	

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Year	Event	Major event
1910	Romanian inventor Henri Coanda builds the Coanda-1910 which he exhibits at the International Aeronautic Salon in Paris. It uses a ducted fan for propulsion instead of a propeller. Years later he claimed that it burned fuel in the duct and was thus a motorjet, but historians debate this claim, and his claims that the aircraft flew in December 1910 before crashing and burning.	
1916	Auguste Rateau suggests using exhaust-powered compressors to improve high-altitude performance, the first example of the turbocharger.	
1917	Sanford Alexander Moss starts work on turbochargers at General Electric, which goes on to be the world leader in this technology.	Label 3
1917	James Stocker Harris patents a "Motor Jet" design on behalf of his brother-in-law Robert Alexander Raveau Bolton.	Label 3
1918	General Electric (GE) starts gas turbine division.	Label 3
1920	W. J. Stern reports to the Royal Air Force that there is no future for the turbine engine in aircraft. He bases his argument on the extremely low efficiency of existing compressor designs. Stern's paper is so convincing there is little official interest in gas turbine engines anywhere, although this does not last long.	Label 3
1921	Maxime Guillaume patents the axial-flow turbine engine. It uses multiple stages in both the compressor and turbine, combined with a single very large combustion chamber. Although sightly different in form, the design is significantly similar to future jet engines in operation.	
1923	Edgar Buckingham at the United States National Bureau of Standards publishes a report on jets, coming to the same conclusion as W. J. Stern, that the turbine engine is not efficient enough. In particular he notes that a jet would use five times as much fuel as a piston engine.	
1925	Wilhelm Pape patents a constant-volume engine design.	
1926	Alan Arnold Griffith publishes his groundbreaking paper 'Aerodynamic Theory of Turbine Design', changing the low confidence in jet engines. In it he demonstrates that existing compressors are "flying stalled", and that major improvements can be made by redesigning the blades from a flat profile into an aerofoil, going on to mathematically demonstrate that a practical engine is definitely possible and showing how to build a turboprop.	Label 4
1927	Aurel Stodola publishes his "Steam and Gas Turbines" - basic reference for jet propulsion engineers in the USA.	
1927	A testbed single-shaft turbocompressor based on Griffith's blade design is tested at the Royal Aircraft Establishment. Known as Anne, the tests are successful and plans are made to build a complete compressor-turbine assembly known as Betty.	
1929	Frank Whittle's thesis on future aircraft design is published. In it he talks about the needs for high-speed flight and the use of turbojets as the only reasonable solution to the problem of propeller efficiency.	Label 5

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Year	Event	Major event
1929	Boris Stechkin publishes first theory of supersonic ramjet, based on compressible fluid theory.	
1930	Whittle presents a complete jet engine design to the Air Ministry. They pass the paper to Alan Griffith at the Royal Aircraft Establishment, who says the idea is impracticable, pointing out a mathematical error, noting the low efficiency of his design, and stating that Whittle's use of a centrifugal compressor would make his proposal useless for aircraft applications.	Label 5
1930	Whittle receives official notice that the Air Ministry is not interested in his concepts, and that they do not even feel that it is worthy of making secret. He is devastated, but friends in the Royal Air Force convince him to patent his design for a gas turbine for jet propulsion anyway. This turns out to be a major stroke of luck, because if the Air Ministry had made the idea secret, they would have become the official owners of the rights to the concept. In his patent, Whittle cleverly hedges his bets, and describes an engine with two axial compressor stages and one centrifugal, thus anticipating both routes forward.	Label 5
1930	Schmidt patents a pulsejet engine in Germany.	
1931	Secondo Campini patents his motorjet engine, referring to it as a thermojet. (A motorjet is a crude form of hybrid jet engine in which the compressor is powered by a piston engine, rather than a turbine)	
1933	Hans von Ohain writes his thesis at the University of Göttingen, describing an engine similar to Frank Whittle's with the exception that it uses a centrifugal "fan" as the turbine as well as the compressor. This design is a dead-end; no "centrifugal-turbine" jet engine will ever be built.	Label 6
1933	Yuri Pobedonostsev and Igor Merkulov tests hydrogen powered GIRD-04 ramjet engine. First supersonic flight of a jet propelled object achieved with artillery-launched ramjets later that year.	
1934	Hans von Ohain hires a local mechanic, Max Hahn, to build his a prototype of his engine design at Hahn's garage.	
1934	Secondo Campini starts work on the Campini Caproni CC.2, based on his "thermojet" engine.	
1935	Whittle allows his patent to lapse after finding himself unable to pay the £5 renewal fee. Soon afterward he is approached by ex-RAF officers Rolf Dudley-Williams and James Collingwood Tinling with a proposal to set up a company to develop his design and Power Jets Ltd is created.	Label 6
1936	Hans von Ohain and Max Hahn of Germany develop and patent their own design.	Label 6
1936	Hans von Ohain is introduced to Ernst Heinkel by a former professor. After being grilled by Heinkel engineers for hours, they conclude his idea is genuine. Heinkel hires Hans von Ohain and Max Hahn, setting them up at their Rostock-area factory.	

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Year	Event	Major event
1936	Junkers starts work on axial-flow turboprop designs under the direction of Herbert Wagner and Adolf Müeller.	
1936	Junkers Motoren (Jumo) is merged with Junkers, formerly separate companies.	
1936	A stationary gas turbine is installed at the Sun Oil refinery in Marcus Hook, Pennsylvania	
1936	French engineer René Leduc, having independently re-discovered René Lorin's design, successfully demonstrates the world's first operating ramjet. The Armée de l'Air orders a prototype aircraft, the Leduc 010, a few months later.	X
1937	Hayne Constant, Griffith's partner at the RAE, starts negotiations with Metropolitan-Vickers (Metrovick), a British heavy industry firm, to develop a Griffith-style turboprop.	X
1937	At Junkers, Wagner and Müller decide to re-design their work as a pure jet.	
1937	April: Whittle's experimental centrifugal engine is tested at the British Thomson-Houston plant in Rugby	Label 6
1937	September: The Heinkel HeS 1 experimental hydrogen fuelled centrifugal engine is tested at Hirth.	
1937	September: Hans von Ohain's Heinkel HeS 1 is converted to run on gasoline. Ernst Heinkel gives the go-ahead to develop a flight-quality engine and a testbed aircraft to put it in.	X
1938	April: Hans Mauch takes over the RLM rocket development office. He expands the charter of his office and starts a massive jet development project, under Helmut Schelp. Mauch spurns Heinkel and Junkers, concentrating only on the "big four" engine companies, Daimler-Benz, BMW, Jumo and Bramo. Mauch and Schelp visit all four over the next few months, and find them uninterested in the jet concept.	
1938	Metrovick receives a contract from the Air Ministry to start work with Constant.	
1938	György Jendrassik starts work on a turboprop engine of his own design.	
1938	A small team at BMW led by Hermann Östrich builds and flies a simple thermojet quickly prompting them to design a true jet engine.	
1938	The Heinkel He 178 V1 jet testbed is completed, awaiting an engine.	
1938	The Heinkel HeS 3 "flight quality" engine is tested. This is the first truly usable jet engine. The engine flies on a Heinkel He 118 later that year, eventually becoming the first aircraft to be powered by jet power alone. This engine is tested until it burns out after a few months, and a second is readied for flight.	Label 6
1938	Wagner's axial-flow engine is tested at Junkers.	
1938	Messerschmitt starts the preliminary design of a twin-engine jet fighter under the direction of Waldemar Voight. This work developed into the Messerschmitt Me 262.	
1939	Arkhip Mikhailovich Lyulka develops early turbofan engine at Kharkov Aviation Institute.	
1939	A stationary gas turbine is installed in a new electrical generating plant in Neuchâtel, Switzerland.	

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Year	Event	Major event
1939	A 2200 horsepower (1600 kW) gas turbine is built by Asea Brown Boveri and used to power an experimental train in Switzerland.	
1939	BMW's team led by Hermann Östrich tests their axial-flow design.	
1939	Bramo starts work on two axial-flow designs, the P.3301 and P.3302. The P.3301 is similar to Griffith's contra-rotating designs, the P.3302 using a simpler compressor/stator system.	
1939	Bramo is bought out by BMW, who abandon their own jet project under Östrich, placing him in charge of Bramo's efforts.	
1939	Summer: Jumo is awarded a contract to develop an axial-flow engine, starting work under Anselm Franz. Müller decamps with half the team to Heinkel.	
1939	Frank Whittle's patent drawing for his engine is published in the German magazine Flugsport.	Label 7
1939	August: the Ernst Heinkel Aircraft company flies the first gas turbine jet plane, the HE178 V1, powered by the HeS 3B.	Label 7
1939	September: A team from the Air Ministry visits Power Jets once again, but this time Frank Whittle demonstrates a jet engine at full power for a continuous 20-minute run. They are extremely impressed, quickly contracts are offered to Whittle to develop a flyable design, and production contracts are offered to practically every engine company in England. These companies also set up their own design efforts, reducing the possibility of financial rewards for Power Jets.	Label 7
1939	September: The Air Ministry also contracts Gloster to build an experimental airframe for testing Whittle's engines, the Gloster E.28/39	Label 7
1939	After hearing of Whittle's successful demonstration, Hayne Constant realises that exhaust thrust is practical. The Metrovick efforts are quickly reworked into a turbojet design, the Metrovick F.2.	X
1939	November: Müller's team restarts work on their axial-flow design at Heinkel, now known as the Heinkel HeS 30.	
1939	René Anxionnaz of France's Rateau (fr) company received a patent on an advanced jet design incorporating bypass.	
1939	Leist joins Daimler-Benz and starts work on an advanced contra-rotating turbofan design, the Daimler-Benz DB 007	
1939	A shakeup at the RLM's engine division places Helmut Schelp in control, and results in development contracts for all existing engine designs. The designs are also given consistent naming, the Heinkel HeS 8 becoming the 109-001, the HeS 30 the -006, BMW's efforts the -002 and -003, and Jumo's the -004. Porsche's project becomes the -005, although work never starts on it. DB gets -007. Numbers starting in the 20s are saved for turboprops, and 500 and up for rockets.	

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Year	Event	Major event
1940	The Campini Caproni CC.2 flies for first time. The flights were highly publicised, and for many years the Italians were credited with having the first jet-powered aircraft.	Label 7
1940	NACA (National Advisory Committee for Aeronautics) starts work on a CC.2 like motorjet for assisted takeoffs, and they later design an aircraft based on it. This work ends in 1943 when turbojets start to mature, and rockets take over the role of JATO, or jet assisted takeoff.	
1940	Hans von Ohain's larger Heinkel HeS 8 (-001) engine is tested.	
1940	BMW's P.3302 (-003) axial-flow engine is tested	
1940	September: Glider testing of the Heinkel He 280 twin-jet fighter begins, while it waits for the HeS 8 to mature.	
1940	September: Henry Tizard visits the United States to show them many of the advanced technologies the British are working on and looking for US production (the Tizard Mission). Among many other details, Tizard first mentions their work on jet engines.	X
1940	October: Rover is selected to build the flight-quality Power Jets W.1. They set up shop at a disused mill in Barnoldswick, but also set up a parallel effort at another factory in Clitheroe staffed entirely by their own engineers. Frank Whittle is incensed.	X
1940	November: The Junkers Jumo 004 axial-flow engine is tested.	
1940	November: Gloster Aircraft Company's proposal for a twin-engine jet fighter is accepted, becoming the Gloster Meteor.	X
1940	December: Whittle's flight-quality W.1X runs for the first time.	Label 7
1940	The Lockheed Corporation starts work on the L-1000 axial-flow engine, the United States's first jet design.	
1940	The Northrop Corporation starts work on the T-37 Turbodyne, the United States's first turboprop design.	
1940	After only two years of development, the Jendrassik Cs-1 turboprop engine is tested. Designed to produce 1000 horsepower (750 kW), combustion problems limit it to only 400 horsepower (300 kW) when it first runs. Similar problems plagued early Whittle designs, but the industry quickly provided assistance. It appears that György Jendrassik had to draw upon any similar talent pool.	
1941	Sir Frank Whittle and the Gloster Aircraft Company design the first successful turbojet, the Gloster Meteor.	X
1941	February: The Air Ministry places an order for 12 Gloster Meteor aircraft.	
1941	February: NACA starts testing their "Propulsive duct engine", a ramjet, unaware of earlier similar efforts. Since ramjets need to be moving in order to work, NACA engineers take the simple step of mounting it at the end of a long arm and spinning it.	
1941	April: The He 280 flies under its own power for first time, powered by two Heinkel HeS 8 (-001) engines. The HeS 8's continue to have reliability issues.	

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Year	Event	Major event
1941	May: The Gloster E.28/39 flies for the first time. Over the next few weeks, the top speed soon passes any existing propeller aircraft.	Label 7
1941	Müller's Heinkel HeS 30 (-006) axial-flow engine runs for first time.	
1941	General Electric is awarded a USAAF contract to develop a turboprop engine, leading to the TG-100 / TG-31 / XT-31 series, and later the J35.	X
1941	Work on the Jendrassik Cs-1 ends. Intended to power a twin-engine heavy fighter, the factory is selected to produce Daimler-Benz DB 605 engines under licence for the Messerschmitt Me 210 instead.	
1941	October: A Power Jets W.2B is sent to General Electric to start production in the US. Sanford Alexander Moss is lured out of retirement to help on the project.	Label 7
1941	The Switzerland turbine-powered train enters testing.	
1942	Dr. Franz Anselm develops the axial-flow turbojet, Junkers Jumo 004, used in the Messerschmitt Me 262, the worlds first operational jet fighter.	X
1942	The Metrovick F.2 is given test rating delivering between 1800 and 2000 lbf (8.9 kN)	
1942	Metrovick start on "thrust augmentation" adding a turbine and propellers to a F2/2 which will lead to the F.3 (a high bypass design) with an extra 1600 lbf (7100 N) over the F2/2.	
1942	Work on the BMW 002 is stopped as it is proving too complex. Work continues on the 003.	
1942	Work on the HeS 8 (-001) and HeS 30 (-006) is stopped, although the later appears to be reaching production quality. Heinkel is ordered to continue on the more advanced Heinkel HeS 011.	
1942	The Messerschmitt Me 262 flies for the first time (later to become the first jet powered combat aircraft to enter service), powered by a Junkers Jumo 211 piston engine in the nose. The BMW 003 has been selected to power the production versions, but is not yet ready for flight tests. The design, offering more internal fuel capacity than the He 280, is selected over its now 003-powered competitor for production.	X
1942	A Jumo 004 flies, fitted to a Messerschmitt Me 110	
1942	The Daimler-Benz 007 axial-flow engine is tested, similar to Griffith's "contraflow" design that uses two contra-rotating compressor stages for added efficiency.	
1942	The "production-quality" BMW 003 is first tested.	
1942	March: The Rover W2B/26 experimental engine (STX) is first run, this was the straight-through design made by Rover without the knowledge of Whittle. This design was to be adopted by Rolls-Royce as the basis for their Derwent engine after they took over from Rover (by which time four more W2B/26 engines were under test).	
1942	The British order a single-engined jet design from de Havilland	
1942	18th July: The Messerschmitt Me 262, the first jet-powered fighter aircraft, flies for the first time under jet power.	Label 7

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Year	Event	Major event
1942	July: Frank Whittle visits the United States to help with General Electric's efforts to build the W.1. The engine is running soon after, known as the "General Electric Type 1", and later as the I-16, referring to the 1600 lbf (7100 N) thrust. They also start work on an improved version, the I-40, with 4000 lbf (18 kN) thrust. The majority of United States jet engines from this time through the mid-1950s are licenced versions of British designs.	X
1942	Whittle returns to Power Jets and starts development of the improved Power Jets W.2/500 and /700 engines, so named for their thrust in kilograms-force (kgf).	
1942	Westinghouse starts work on an axial-flow engine design, the WE-19.	
1942	October: The Bell XP-59 flies, powered by a General Electric Type I-A (W.1).	X
1942	The Fieseler Fi 103 V-1 pulsejet powered "flying bomb" (cruise missile) flies for the first time.	X
1942	Armstrong Siddeley starts work on an axial-flow design, the ASX.	
1942	December: After a meeting held at a pub, Rover agrees to hand over the jet development to Rolls-Royce, in exchange for their Rolls-Royce Meteor tank engine factory.	X
1943	1st January: Rolls takes over the Rover plants, although the official date is several months later. Stanley Hooker leads a team including Fred Morley, Arthur Rubbra and Harry Pearson. Several Rover engineers decide to stay on as well, including Adrian Lombard, leader of Rover's "offshoot" design team. They focus on making the W.2B production quality as soon as possible.	
1943	After only a few short months since Rolls-Royce took over from Rover, the W.2B/23, soon to be known as the Rolls-Royce Welland, starts production.	
1943	The parallel Rover design effort, the W.2B/26, is adopted by Rolls-Royce for further development and becomes the Rolls-Royce Derwent.	
1943	The de Havilland Goblin engine is tested, similar in most ways to the Derwent.	
1943	March: A licence for the Goblin is taken out in the United States by Allis-Chalmers, later becoming the J36. Lockheed is awarded a contract to develop what would become the P-80 Shooting Star, powered by this engine.	
1943	Production of Jumo 004B starts.	
1943	Production of BMW 003A starts.	
1943	First running turbofan the German Daimler-Benz DB 670 (aka 109-007) operated on its testbed on April 1, 1943	Label 7
1943	Throughout 1943, the Jumo 004 and BMW 003 continue to destroy themselves at an alarming rate due to turbine failures. Efforts in the United Kingdom, at one point years behind due to official indifference, have now caught up due to the availability of high temperature alloys which allowed for considerably more reliable high-heat sections of their designs.	
1943	Design work on the BMW 018 starts.	

Continued on next page

Table A13 – continued from previous page

Year	Event	Major event
1943	The US decides to rename all existing jet projects with a single numbering scheme. The L-1000 becomes the J37, GE's Type I the J31, and Westinghouse's WE-19 the J30. Newer projects are fitted into the remaining "30's". Turboprop designs become the T series, also starting at 30.	
1943	June: Metrovick F.2/1 tested, fitted to Avro Lancaster	
1943	September: Allis-Chalmers runs into difficulty on the J36, and the Shooting Star project is re-engined with the General Electric J33, a licenced version of the W.2B/26, or Rolls-Royce Derwent. GE later modifies the design to produce over twice the thrust, at 4000 lbf (18 kN).	
1943	Frank Whittle's W.2B/700 engine is tested, fitted to a Vickers Wellington Mk II bomber.	
1943	March: Westinghouse's X19A axial-flow engine is bench tested at 1165 lbf (5180 N).	
1943	Miles Aircraft test an all-moving tailplane as part of the Miles M.52 supersonic research aircraft design effort.	
1943	A Welland-powered prototype Gloster Meteor flies.	
1943	The Goblin-powered de Havilland Vampire flies.	
1943	Lyul'ka VDR-2 axial-flow engine tested, the first Soviet jet design.	X
1943	The General Electric J31, their version of the W.2B/23, is tested.	
1943	November: The Metrovick F.2 is tested on a modified Gloster Meteor. Although more powerful, smaller and more fuel efficient than the Welland, the design is judged too complex and failure prone. In his quest for perfection, Griffith instead delivers an impractical design. Work continues on a larger version with an additional compressor stage that over doubles the power.	
1943	The Armstrong Siddeley ASX is tested.	
1943	Metrovick F2/3 delivers 2700 lbf (12000 N) but not developed further, moving on to 10 stage F2/4.	
1944	BMW tests the 003R, a 003 with an additional rocket engine for them and produce an even more powerful engine. In a short 6-month period Rolls-Royce design and build the Nene at 5000 lbf (22 kN), but it sees only limited use in the United Kingdom.	
1944	April: With internal design efforts under way at most engine companies, Power Jets have little possibility of profitability, and are nationalised, becoming a pure research lab as the National Gas Turbine Establishment.	Label 7
1944	June: Design work on a gas turbine engine for powering tanks begins under the direction of Müller, who left Heinkel in 1942. The first such system, the GT 101, is completed in November and fitted to a Panther tank for testing.	X
1944	June: A Derwent II engine is modified with an additional turbine stage powering a gearbox and five-bladed propeller. The resulting RB.50, or Rolls-Royce Trent, is not further developed, but is test flown on a modified Gloster Meteor.	
1944	The Junkers Ju 287 jet bomber is tested.	

Continued on next page

Table A13 – continued from previous page

Year	Event	Major event
1944	The BMW 018 engine is tested. Work ends soon after when the entire tooling and parts supply are destroyed in a bombing raid.	
1944	The Junkers Jumo 012 engine is tested, it stands as the most powerful engine in the world for some time, at 6600 lbf (29000 N).	
1944	The J35, a development of an earlier turboprop effort, runs for the first time.	
1944	Ford builds a copy of the V-1's engine, known as the PJ-31-1.	
1944	The Ishikawajima Ne-20 first runs in Japan. Originally intending to build a direct copy of the BMW 003, the plans never arrived and the Japanese engineers instead built an entirely new design based on a single cutaway image and several photographs.	X
1944	The Doblhof WNF-4 flies, the first ramjet-powered helicopter.	X
1944	5th April: The nearly complete prototype of the Leduc 010 ramjet-powered aircraft, under construction at the Montaudran airfield near Toulouse, France unbeknownst to German occupation authorities, is heavily damaged by a Royal Air Force bombing raid.	
1944	April: The Messerschmitt Me 262 first enters combat service in Germany.	X
1944	June: The Messerschmitt Me 262 enters squadron service in Germany.	
1944	July: The Gloster Meteor enters squadron service in the United Kingdom.	Label 7
1944	27th July: First combat mission flown by a Gloster Meteor	X
1944	4th August: Gloster Meteors shot down two pulsejet-powered V-1 flying bombs	X
1944	An effort starts in Germany to build a simple jet fighter, the Volksjäger. The contract is eventually won by the Heinkel He 162, to be powered by the BMW 003.	
1944	December: Northrop's T-37 turboprop is tested. The design never matures and work is later stopped in the late 1940s.	
1945	The Nakajima Kikka flies for the first time on August 7, 1945, powered by two Ishikawajima Ne-20 turbojets, making it the first Japanese jet aircraft to fly.	X
1945	Stanley Hooker scales the Nene down to Gloster Meteor size, producing the RB.37, also referred to, confusingly, as the Derwent V. A Derwent V powered Meteor sets the world speed record at 606 mph at the end of the year. The importance of this incident relegates the development of more powerful engines unimportant.	Label 7
1945	The Junkers 022 turboprop runs.	
1945	An afterburner equipped Jumo 004 is tested.	
1945	Lyul'ka VDR-3 axial-flow engine tested.	
1945	Lyul'ka TR-1 axial-flow engine tested.	
1945	The RB.39 Rolls-Royce Clyde turboprop runs, combining axial and centrifugal stages in the compressor. Rolls-Royce abandon development, preferring to focus on the turbojet. A carrier-based naval strike aircraft, the Westland Wyvern, having already changed from its original Rolls-Royce Eagle piston engine, uses the alternative turboprop, the Armstrong Siddeley Python.	

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Table A13 – continued from previous page

Year	Event	Major event
1945	The Avia S-92, a version of the Me 262, is built in Czechoslovakia.	
1946	January: A dispirited Frank Whittle resigns from what is left of Power Jets. Gradually the company is broken up, with only a small part remaining to administer its patents.	X
1946	Development of the Rolls-Royce Dart starts. The Dart would go on to become one of the most popular turboprop engines made, with over 7000 being produced before the production lines finally shut down in 1990.	
1946	Metrovick F2/4 Beryl delivers 4000 lbf (17.8 kN). Metrovick jet turbines sold to Armstrong Siddeley.	
1948	First turbojet breaks sound barrier.	Label 8
1949	First use of turbojet for commercial service.	Label 8
1949	21st April: The Leduc 010, the world's first ramjet powered aircraft, finally completes its maiden flight in Toulouse, France. The aircraft's rate of climb exceeds that of the best contemporary turbojet powered fighters.	X
1949	22nd June: Vickers VC.1 Viking flew with Rolls-Royce Nene turbojets: the world's first pure jet transport aircraft.	X
1950	Late 1950: Rolls-Royce Conway the world's first production turbofan enters service, significantly improving fuel efficiency and paving the way for further improvements.	X
1952	2nd May: Powered by the Rolls-Royce Avon (first axial flow jet engine), the De Havilland Comet is the first commercial jetliner to enter service with British Overseas Airways Corporation (BOAC)	Label 9
1953	The de Havilland Gyron, Halford's last jet design, runs for the first time. Before cancellation 2 years later it has evolved to 25000 lbf (110000 N) using reheat. Other comparable turbojet engines are developed at the same time including the Canadian Orenda Iroquois.	
1955	First use of reheat to increase thrust of turbojet.	X
1956	15th September: the Tu-104 medium range jet airliner enters service with Aeroflot, the world's first jet airliner to provide a sustained and successful service. The Tu-104 was the sole jetliner operating in the world between 1956 and 1958.	
1958	October: the Boeing 707 enters service with Pan American. This aeroplane is largely credited with ushering in the Jet Age having huge commercial success with few operating problems unlike its competitors. This plane helped establish Boeing as one of the leading makers of passenger aircraft in the world.	Label 10
1959	Sud Aviation Caravelle enters service: claimed as the first short/medium range jet airliner, first flight 27 May 1955.	
Late 1950s	The General Electric CJ805 and Pratt & Whitney JT3C are the first low-bypass turbofan engines on offer on commercial aircraft including the Convair 880, Boeing 707 and Douglas DC-8.	

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Table A13 – continued from previous page

Year	Event	Major event
1968	30th June: TF39 high bypass turbofan of 43300 lbf (193 kN) enters service on the C-5 Galaxy transport ushering in the age of wide-body transports.	
1968-70	The GE TF39 high bypass turbofan fitted on the Lockheed C-5 Galaxy is developed into the CF6.	
1969	2nd March: First flight of Concorde.	Label 11
1970	The Rolls-Royce RB211 engine which features titanium fan blades & three-spool technology enters service on the Boeing 747 and the Lockheed L-1011 TriStar.	
1974	The CFM International joint venture between General Electric and Snecma (Safran) is founded.	X
1975	26th December: Tu-144S the first supersonic jet airliner went into mail and freight service between Moscow and Alma-Ata in preparation for passenger services, which commenced November 1977.	Label 12
1976	The Rolls-Royce/Snecma Olympus 593-powered supersonic airliner Concorde enters service.	
1976	21st January: Concorde, the supersonic jet airliner, enters passenger service with British Airways and Air France.	Label 12
1978	1st June: Tu-144 withdrawn from scheduled passenger service after 55 passenger flights due to reliability and safety problems.	
Early 1980s	The CFM56 is selected for the Boeing 737 Classics - 300/400/500.	
1983	4th October: Thrust2 turbojet-powered car gets the land speed record to 1149 km/h.	Label 13
Late 1980s	Open rotor experiments are conducted by GE on the GE36 and P&W/Allison on the 578DX featuring unducted fan (UDF) technology.	
1995	The Boeing 777 powered by the GE90 which features composite fan blades enters service with United Airlines.	
1997	15th October: ThrustSSC first supersonic car, powered by two turbofans takes the land speed record to 1228 km/h.	Label 14
2002	HyShot scramjet ignited and operated.	Label 15
2003	31st January: GE90-115B receives FAR 33 certification; currently holds the world record for thrust and engine (fan) size for a gas turbine powered engine at 127900 lbf of thrust and 128 inches, respectively.	
2003	26th November: Concorde retires from service.	
2004	Hyper-X first scramjet to maintain altitude.	X
2007	Hyper-X first airbreathing (scram)jet to attain Mach 10.	Label 16
Late 2000s	The Pratt & Whitney PW1000G geared turbofan is developed.	

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Table A13 – continued from previous page

Year	Event	Major event
Late 2000s	The Leap-1A features CMC technology on its turbine shroud.	

Table A14: Timeline of wind energy [EIA, 2008e]

Year	Event	Major event
500-900 AD	The first windmills were developed in Persia for pumping water and grinding grain.	
1185	Earliest confirmed reference to a windmill, in Weedley, Yorkshire	
c. 1300	The first horizontal-axis windmills (i.e. pinwheel) appeared in Western Europe.	
14th century	Dutch windmills used to drain areas of the Rhine River delta.	X
18th century	Windmills used to pump water for salt making on the island of Bermuda and on Cape Cod during the American revolution.	
1850s	Daniel Halladay and John Burnham worked to build and sell the Halladay Windmill, designed for the American West. It had an open tower design and thin wooden blades. They also started the U.S. Wind Engine Company.	Label 1
Late 1880s	Thomas O. Perry conducted over 5000 wind experiments trying to build a better windmill. He invented the mathematical windmill, which used gears to reduce the rotational speed of the blades. This design had greater lifting power and smoother pumping action, and the windmill could operate in lighter winds. Perry also started the Aermotor Company with LaVerne Noyes.	Label 2
Late 1880s	The development of steel blades made windmills more efficient. Six million windmills sprang up across America as settlers moved west. Homesteaders purchased windmills from catalogues or travelling salesmen or, otherwise, built their own. Mills were used to pump water, shell corn, saw wood, and mill grain.	Label 2
1887	The first windmill used for the production of electricity was built in Scotland in July 1887 by Prof James Blyth of Anderson's College, Glasgow.	Label 2
1888	Charles F. Brush created the first large windmill to generate electricity in the U.S. in Cleveland, Ohio. Windmills that produce electricity started to be called wind turbines. In later years, General Electric acquired Brush's company, Brush Electric Co.	Label 2
1891	The Danish scientist Poul la Cour constructed a wind turbine to generate electricity, which was used to produce hydrogen by electrolysis to be stored for use in experiments and to light the Askov High school. He later solved the problem of producing a steady supply of power by inventing a regulator, the Kratostate.	Label 3
1893	In Chicago, Illinois, the World's Columbian Exposition (also known as the Chicago World's Fair) highlighted 15 windmill companies that showcased their goods.	
1895	Poul la Cour converts his windmill into a prototype electrical power plant that was used to light the village of Askov.	Label 3
Early 1900s	Windmills in California pumped salt-water to evaporate ponds. This provided gold miners with salt.	
1927	Brothers Joe and Marcellus Jacobs open a factory, Jacobs Wind in Minneapolis to produce wind turbine generators for farm use.	Label 4

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Table A14 – continued from previous page

Year	Event	Major event
1931	Darrieus wind turbine invented, with its vertical axis providing a different mix of design tradeoffs from the conventional horizontal-axis wind turbine. The vertical orientation accepts wind from any direction with no need for adjustments, and the heavy generator and gearbox equipment can rest on the ground instead of atop a tower.	Label 4
1936	The U.S. starts a rural electrification project that removes the natural market for wind-generated power, since network power distribution provided a farm with more dependable usable energy for a given amount of capital investment.	Label 5
1941	For several months during World War II, the Smith-Putnam wind turbine supplied power to the local community at “Grandpa’s Knob”, a hilltop near Rutland, Vermont. Its blades were 53 metres (175 feet) in diameter, and this became the world’s first windmill to provide utility scale (i.e. greater than 1 MW) power levels.	Label 6
1943	The Smith-Putnam wind turbine broke down, and the machine was shut down.	
1945	The Smith-Putnam machine was restarted, but small cracks in the blade caused one blade to break; the turbine was shut down forever.	
1950s	Most windmill companies in the United States went out of business.	Label 7
1973	The Organization of Petroleum Exporting Countries (OPEC) oil embargo caused the prices of oil to rise sharply. High oil prices increased interest in other energy sources, such as wind energy.	Label 8
1974-82	With funding from the National Science Foundation and the U.S. Department of Energy, the National Aeronautics and Space Administration (NASA) led an effort to increase wind power technology at the Lewis Research Center in Cleveland , Ohio. NASA developed 13 experimental wind turbines with four major designs: 1. the MOD-0A (200 kilowatts), 2. the MOD-1 (2 megawatts, the first U.S. turbine in 1979 over 1 megawatt), 3. the MOD-2 (2.5 megawatts), 4. the MOD-5B (3.2 megawatt).	Label 8
1978	Congress passed the Public Utility Regulatory Policies Act (PURPA) of 1978 to encourage the use of renewable energy and cogeneration facilities (plants that have another purpose besides producing electricity). PURPA requires utility companies to buy extra electricity from renewable and cogeneration facilities that meet certain qualifications, called qualifying facilities (QFs). The amount that a utility pays a QF must be equal to the cost that it would have taken the utility to produce the same amount of electricity, called the avoided cost.	Label 9
1978	The world’s first multi-megawatt wind turbine was constructed by teachers and students of the Tvind school in Denmark.	Label 9
1979	The first U.S. wind turbine rated over 1 megawatt (MOD-1) began operating; MOD-1 had a 2-megawatt capacity rating.	Label 9
1979	The cost of electricity from wind generation was about 40 cents per kilowatt hour.	

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Table A14 – continued from previous page

Year	Event	Major event
1980	The Crude Oil Windfall Profits Tax Act of 1980 further increased tax credits for businesses that used renewable energy. The Federal tax credit for wind energy reached 25%, rewarding those businesses choosing to use renewable energy.	Label 9
1983	Because of a need for more electricity, California began using a contract system that allowed certain renewable and cogeneration facilities (or in other words, QFs) to lock into rates that would make electricity generated from renewable technologies, like wind farms and geothermal plants, more cost competitive. Prices were based on the costs saved by not building planned coal plants.	Label 10
1985	Many wind turbines were installed in California in the early 1980s to help meet growing electricity needs and to take advantage of government incentives. By 1985, California wind capacity exceeded 1000 megawatts, enough power to supply 250000 homes. These wind turbines were very inefficient.	
1987	The MOD-5B was the largest wind turbine operating in the world — with a rotor diameter of nearly 100 metres (330 feet) and a rated power of 3.2 megawatts.	X
1988	Many of the hastily installed turbines of the early 1980s were removed and later replaced with more reliable models.	
1989	Throughout the 1980s, U.S. DOE funding for wind power research and development declined, reaching its low point in 1989.	Label 10
1990	More than 2200 megawatts of wind energy capacity was installed in California — more than half of the world's capacity at the time.	
1992	The U.S. Energy Policy Act of 1992 called for increased energy efficiency and renewable energy use and authorised a production tax credit of 1.5 cents per kilowatt hour for wind-generated electricity. It also reformed the Public Utility Holding Company Act to help make smaller utility companies more able to compete with larger ones.	Label 11
1993	U.S. Windpower developed one of the first commercially available variable-speed wind turbines, the 33M-VS. The development was completed over five years, with the final prototype tests completed in 1992. The $20-million project was funded mostly by U.S. Windpower, but also involved Electric Power Research Institute (EPRI), Pacific Gas & Electric, and Niagara Mohawk Power Company.	Label 11
1995	In a ruling against the California Public Utility Commission, the Federal Energy Regulatory Commission (FERC) refused to allow utilities to pay qualifying renewable facilities (QFs) rates that were higher than the utilities' avoided cost, the amount that it would cost the utility to produce the same amount of electricity.	
1995	The U.S. Department of Energy's (DOE) Wind Energy Program lowered technology costs. DOE's advanced turbine program led to new turbines with energy costs of 5 cents per kilowatt hour of electricity generated.	Label 11

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Table A14 – continued from previous page

Year	Event	Major event
Mid-1990s	Ten-year Standard Offer contracts written in the U.S. during the mid-1980s (at rates of 6 cents per kilowatt hour and higher) began to expire. The new contract rates reflected a much lower avoided cost of about 3 cents per kilowatt hour and created financial hardships for most qualifying renewable and cogeneration facilities (QFs).	
Mid-1990s	Kenetech, the producer of most of the U.S.-made wind generators, faced financial difficulties; it sold off most of its assets and stopped making wind generators.	
1999	Wind generated electricity reached the 2000 megawatt mark.	
1999-2000	Installed capacity of wind-powered, electricity-generating equipment exceeded 2500 megawatts. Contracts for new wind farms continued to be signed.	
1999-2001	The cost of electricity from wind generation was from 4 to 6 cents per kilowatt hour.	
2003	Installed capacity of wind-powered, electricity-generating equipment was 4685 megawatts as of January 21.	
2004	The cost of electricity from wind generation was 3 to 4.5 cents per kilowatt hour.	
2005	The U.S. Energy Policy Act of 2005 strengthened incentives for wind and other renewable energy sources.	Label 12
2006	U.S. DOE's budget for wind subsidies was about $500 million — about 10 times as much as the 1978 level.	
2007	Wind power provided 5 percent of the renewable energy used in the United States.	
2007	U.S. wind power produced enough electricity, on average, to power the equivalent of over 2.5 million homes.	
2007	Installed capacity of wind-powered, electricity-generating equipment was 13885 megawatts as of September 30 — more than four times the capacity in 2000.	
2009	The world's first operational deep-water large-capacity floating wind turbine, Hywind, became operational in the North Sea off Norway in late 2009 at a cost of some 400 million kroner (around US$62 million) to build and deploy.	Label 13
2011	In late 2011, Japan announced plans to build a multiple-unit floating wind farm, with six 2-megawatt turbines, off the Fukushima coast of north-east Japan where the 2011 tsunami and nuclear disaster has created a scarcity of electric power.	
2015	Largest wind turbines measure 8MW capacity. These are the Vestas V164 for offshore use.	

Table A15: Timeline of wireless data transfer [Wireless History Foundation, 2018]

Year	Event	Major event
1896	Guglielmo Marconi develops the first wireless telegraph system.	X
1927	First commercial radiotelephone service operated between Britain and the U.S.	X
1946	The first commercial mobile radiotelephone service is introduced in St. Louis.	X
1947	The transistor is invented by scientists John Bardeen, Walter Brattain and William Shockley who later share the Nobel Prize. The transistor replaces vacuum tubes, serving as the foundation for the development of modern electronics and makes possible the marriage of computers and communications.	X
1947	Engineers at Bell Labs develop the concept of cellular technology.	X
1948	Claude Shannon publishes two benchmark papers on Information Theory, containing the basis for data compression (source encoding) and error detection and correction (channel encoding).	X
1950	TD-2, the first terrestrial microwave telecommunication system, is installed to support 2400 telephone circuits.	
1962	The first communication satellite, Telstar, is launched into orbit.	X
1964	The International Telecommunications Satellite Consortium (INTELSAT) is established.	X
1964	AT&T's Improved Mobile Telephone Service (IMTS) eliminates the need for push-to-talk operation and offers automatic dialling.	
1965	INTELSAT launches the Early Bird geostationary satellite.	
1968	The Defense Advanced Research Projects Agency – US (DARPA) selects BBN to develop the Advanced Research Projects Agency Network (ARPANET), precursor of the modern Internet.	X
1968	The Federal Communications Commission (FCC) opens Docket 18262 to set aside sufficient spectrum to meet the demand for land mobile communications. Congestion on the frequencies then available was approaching unacceptable levels, with a waiting period of several years in some markets to get a mobile phone.	X
1970	The FCC allocates 75 MHz for common carrier cellular systems out of the UHF spectrum.	X
1971	June: ALOHAnet connected the Hawaiian Islands with a UHF wireless packet network. ALOHAnet and the ALOHA protocol were early forerunners to Ethernet, and later the IEEE 802.11 protocols, respectively.	X
1971	The FCC modifies its 1970 decision to allow non-wireline carriers (non-telephone companies) as well as wireline (telephone) carriers to access the 75 MHz allocated for common carrier radio cellular systems.	X
1974	The FCC revises it cellular allocation from 75 MHz to 40 MHz, restricts eligibility to wireline carriers, and adopts a one system per market policy because of its belief that technical complexity and expense would make competing systems in a market unviable. The FCC also decides to licence developmental systems.	

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Table A15 – continued from previous page

Year	Event	Major event
1977	FCC authorises developmental cellular systems launch in Chicago and the Washington, D.C./Baltimore region.	
1981	FCC issues Cellular Communications Systems Order, determining the cellular industry should have two carriers per market and creates cellular “A” and “B” licences for each area of the country.	
1982	AT&T settles its antitrust lawsuit with the U.S. Government, agreeing to divest itself of local phone service and its cellular licences.	
1982	In June, the FCC accepts 190 applications for the 30 largest markets in the United States. Only 3 applications were received for Boston, the smallest number for the major markets.	
1982	In November, the FCC accepts 353 applications for markets 31-60.	
1983	January: TCP/IP is selected as the official protocol for the ARPANET.	Label 1
1983	Motorola introduces the DynaTAC mobile telephone unit, the first truly “mobile” radiotelephone. The phone, dubbed the “brick”, had one hour of talk time and eight hours of standby.	Label 1
1983	In March, the FCC accepts 567 applications for markets 61-90. The FCC states this is too many applications to handle effectively by comparative hearings, and in October issues a rulemaking seeking authority to award licences by lottery.	
1983	13th October: the first commercial cellular system begins operating in Chicago. In December 1983, the second system is activated in the Baltimore/Washington, D.C. corridor.	Label 1
1984	February: cellular service launches in Indianapolis as the third U.S. market with coverage.	
1984	The Cellular Telecommunications Industry Association is founded in May.	
1984	In July, the FCC is inundated with 5182 applications for markets 91-120, after having received only 1110 applications for the 90 largest markets in the country.	
1984	The divestiture of AT&T is finalised, with cellular operations going to the seven Regional Bell Operating Companies. AT&T National AMPS company is divided among the RBOCS.	
1985	The FCC releases the ISM band for unlicenced use, paving the way for wireless local area networking. These frequency bands are the same ones used by equipment such as microwave ovens and are subject to interference.	
1985	At year’s end, there are 340213 cell phone subscribers.	
1986	In February, the FCC receives 8007 applications for markets 121-135 and 7436 applications for markets 136-150.	
1986	In March, the FCC receives 6367 applications for markets 151-165.	
1986	In April, the FCC receives 8471 applications for markets 166-180, and 25018 for markets 181-240.	
1986	In May, the FCC accepts 37650 applications for markets 241-305. At some point during this year, the shelves in the FCC filing room allegedly collapse due to the weight of the 100000 applications in storage.	

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Table A15 – continued from previous page

Year	Event	Major event
1987	One millionth cellular subscriber is added in October.	X
1988	FCC's Auxiliary Cellular Services Order adopts technical flexibility rules for cellular radio without mandating specific standards, which promotes the introduction of advanced cellular technologies by the industry.	Label 2
1989	The "technology wars" among competing digital cellular standards begin.	Label 2
1989	The Motorola MicroTAC is introduced, the smallest and lightest phone available at the time, weighing 12.3 ounces.	
1990	Cellular subscribership surpasses 5 million.	
1990	Fleet Call, announces plans to build digital market-wide systems, functionally equivalent to cellular but on adjacent frequencies formerly reserved for private radio systems, in Chicago, Dallas, Houston, LA, New York and San Francisco and asks the FCC for rule waivers.	
1991	NCR Corporation with AT&T Corporation invented the precursor to 802.11, intended for use in cashier systems, under the name WaveLAN.	X
1991	The industry Fraud Task Force is launched.	
1991	CTIA begins the Certification Seal program for cellular equipment.	
1992	The number of cellular users passes the 10 million milestone.	Label 3
1992	World's first commercial text message is sent by employees of Logica CMG.	Label 3
1992	One-millionth host connected to the Internet, with the size now approximately doubling every year.	Label 3
1992 & 1996	The Australian radio-astronomer Dr John O'Sullivan with his colleagues Terence Percival, Graham Daniels, Diet Ostry, John Deane developed a key patent used in Wi-Fi as a by-product of a Commonwealth Scientific and Industrial Research Organisation (CSIRO) research project, "a failed experiment to detect exploding mini black holes the size of an atomic particle". Dr O'Sullivan and his colleagues are credited with inventing Wi-Fi. In 1992 and 1996, CSIRO obtained patents for a method later used in Wi-Fi to "unsmear" the signal.	Label 3
1993	Congress adopts Omnibus Budget Reconciliation Act of 1993, which establishes national framework for wireless regulation and authorises FCC to auction spectrum for the first time.	Label 3
1993	The first smart phone (IBM's Simon) is released to the public and offers consumers a calendar, address book, calculator, email, faxing services and games.	Label 3
1993	Internet Protocol version 4 (IPv4) established for reliable transmission over the Internet in conjunction with the Transport Control Protocol (TCP).	Label 3
1994	FCC begins licensing Personal Communication Services (PCS) spectrum (1.7 to 2.3 GHz). The licence auction raises $7.7 billion for the U.S. Treasury.	
1995	There are more than 33.8 million wireless subscribers, representing approximately 13% of the total U.S. population.	
1995	Sprint Spectrum launches the first PCS system in the United States in Washington, D.C.	

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Table A15 – continued from previous page

Year	Event	Major event
1996	The Telecommunications Act of 1996 becomes law, in part designed to open other communications markets to competition.	Label 4
1997	Original version of the standard IEEE 802.11 protocol for wireless local area networking is released, providing up to 2 Mbit/s link speeds.	Label 4
1997	The wireless industry unveils its "Safety – Your Most Important Call" to help educate drivers about the dangers of distracted driving.	
1997	Balanced Budget Act of 1997 calls for auctioning additional commercial spectrum by Sept, 2002. Advanced Wireless services (AWS-1) auction concludes Sept. 18, 2006, raising nearly $14 billion for U.S. Treasury.	
1998	Ericsson, IBM, Intel, Nokia, and Toshiba announce they will join to develop Bluetooth for wireless data exchange between handheld computers or cellular phones and stationary computers.	
1998	The first "bucket" of minutes plan is offered.	
1999	802.11 protocol was updated in 1999 with 802.11b to permit 11 Mbit/s link speeds, which proved to be popular.	
1999	Wi-Fi Alliance® founded by six companies as a trade association to hold the Wi-Fi trademark under which most products are sold: 3Com, Aironet, Intersil, Lucent Technologies, Nokia and Symbol Technologies.	Label 5
1999	Wi-Fi® brand adopted for technology based upon IEEE 802.11 specifications for wireless local area networking.	
1999	With the Wireless Communications and Public Safety Act of 1999, Congress designates 911 as the universal emergency number of wireline and wireless service and promotes the use of technologies that help public safety service providers locate wireless 911 callers.	
2000	Wireless subscribership in America exceeds 100 million, totalling approximately 38% of the U.S. population.	
2000	Digital wireless users outnumber analog subscribers.	Label 5
2000	The Cellular Telecommunications Industry Association merges with the Wireless Data Forum to become the Cellular Telecommunications & Internet Association.	
2001	The average wireless consumer uses his or her phone for 320 minutes per month.	
2001	8th November: FCC votes to raise CMRS spectrum limits for individual carriers from 45 MHz to 55 MHz, and subsequently eliminate cap in January 2003.	
2002	Camera phones are first introduced in the U.S. market.	X
2003	With the Secondary Markets Order, the FCC creates a "secondary market" which permits licencees to lease any amount of their spectrum.	
2004	The Cellular Telecommunications & Internet Association changes its name to CTIA-The Wireless Association®.	

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Table A15 – continued from previous page

Year	Event	Major event
2004	Congress enacts the Commercial Spectrum Enhancement Act, creating the Spectrum Relocation Fund to recover the costs associated with relocating radio communication systems from certain bands.	
2005	Spurred by the Hurricane Katrina disaster, the wireless industry, together with the American Red Cross, develops the national Text 2Help Initiative, which allows customers to donate $5 via text message in the event of a major disaster.	
2005	Deficit Reduction Act of 2005 enables Digital TV Transition and directs auctioning of 700 MHz of spectrum licences. Auction concludes March, 2006, raising almost $19 billion for the U.S. Treasury.	
2005	Subscribership reaches nearly 208 million, which is approximately 69% of the total U.S. population.	
2005	Subscribers use more than 1.5 trillion voice minutes and send and receive more than 81 billion SMS messages.	
2005	Wi-Fi chipset shipments top 100M annually.	Label 6
2006	Aircell successfully bids $31.3 million for FCC air-to-ground broadband frequency licence.	
2006	Google announces on October 9 that it has bought YouTube for $1.65 billion.	
2007	iPhone launches, spurring dramatic handset innovation.	Label 7
2008	There are more than 270 million wireless subscribers who use more than 2.2 trillion minutes; more than 1 trillion SMS messages are sent and received in the U.S.	
2008	iTunes Application Store (July) and Android Market (October) open.	Label 7
2008	13th October marks the 25th anniversary of commercial wireless communications and the launch of the Wireless History Foundation.	
2009	Wi-Fi uses a large number of patents held by many different organizations. In April 2009, 14 technology companies agreed to pay CSIRO $1 billion for infringements on CSIRO patents. This led to Australia labelling Wi-Fi as an Australian invention, though this has been the subject of some controversy.	X
2009	There are more than 285.6 million U.S. wireless subscriber connections which is approximately 91% of the total U.S. population.	
2009	Wireless subscribers use more than 6.2 billion minutes per day and send and receive more than 5 billion SMS messages per day.	
2009	Palm Software Store (January), BlackBerry App World (April), Nokia Ovi Store (May), Palm App Catalog (June) and Windows Mobile Marketplace (July) app stores open.	
2009	One billionth Wi-Fi chipset is sold.	Label 8
2010	First 4G handset is introduced at International CTIA WIRELESS show.	
2010	After the devastating January earthquake in Port-au-Prince, Haiti, a record-breaking $35 million is donated via text message.	

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Table A15 – continued from previous page

Year	Event	Major event
2010	FCC proposes National Broadband Plan, recommending 500MHz of spectrum be allocated for commercial use by 2020.	
2010	June: President Barack Obama signs a memorandum committing to freeing up 500 MHz of spectrum for the wireless industry.	Label 8
2010	October: the Inaugural Wireless Hall of Fame dinner is held in San Francisco to induct new members and recognise previous inductees for their substantial contributions to the wireless industry.	
2012	CSIRO won a further $220 million settlement for Wi-Fi patent-infringements in 2012 with global firms in the United States required to pay the CSIRO licensing rights estimated to be worth an additional $1 billion in royalties.	
2016	The wireless local area network Test Bed was chosen as Australia's contribution to the exhibition 'A History of the World in 100 Objects' held in the National Museum of Australia.	

Appendix B - Validation themes survey

Thank you for taking the time to complete this survey. This survey consists of 60 questions, and should take approximately 20 minutes to complete.

As a thank you for participating in this survey the results of this research will be distributed (following publication) to any respondents who wish to make use of this analysis in their own work (simply provide a contact email address with your responses, or leave blank if you do not wish to receive any further follow-up).

Forecasting changes

Simulated forecasts govern much of our lives (from predictions of the next week's weather, to projections of a nation's financial outlook, or warnings of traffic congestion as holiday-makers head away to the sun). However, our reaction to the information presented, and whether we choose to believe the predictions made depends greatly on the evidence that is displayed, and the credibility of the methods that are used to model these future scenarios. Equally, this depends on the manner in which the information is presented. The aim of this survey is to try to establish which factors are most critical in establishing the credibility of changes predicted by forecasts, and how existing modelling and simulation techniques fare when presented to different audiences.

This research forms part of a doctoral thesis examining the impact of disruptive innovations in Air Transportation (sponsored by Airbus Operations Ltd and the University of Bristol). The responses gathered in this survey will be used to assess the credibility of different forms of evidence for validating computer-generated forecasts, with the intention to publish the results of this analysis in academic journals.*

1. *All personal data collated in this survey will be processed in accordance with the Data Protection Act 1998. It will be stored electronically on Typeform's secure encrypted servers, for no longer than 2 years after the deadline for completion of the survey (1st August 2015), after which it will be permanently deleted. During this time, it will only be accessible by the principal researcher and will not be passed to any third parties without express written consent from the data subject (i.e. you). The personal data will be processed for the purpose of creating anonymous demographic information to accompany the results of the survey. Please tick the box marked "I accept" below to confirm that you are content for your personal data to be processed in this way.*

   Yes - I accept
   No - I do not accept

Personal Details

2. What is your name?
   (Leave blank if you do not wish to receive a copy of the anonymised final results)

3. What is your contact email address?
   (Leave blank if you do not wish to receive a copy of the anonymised final results)

4. Which age category are you?*
   A 24 or less
   B 25 to 34
   C 35 to 44
   D 45 to 54
   E 55 to 64
   F 65+

5. Are you male or female?*
   A Male
   B Female

6. Which domain(s) best describes your current occupation?*
   (Choose as many as you like)
   A Academic
   B Commercial
   C Full-time education
   D Industrial
   E Part-time education
   F Public sector

G Self-employed
H Unemployed
I Other

7. Which description best describes your place of work/study?*
   A Small organisation (i.e. 10s of members)
   B Medium organisation (i.e. 100s of members)
   C Large organisation (i.e. 1,000s of members)
   D Not part of an organisation (unemployed/self-employed)

8. Would you describe yourself as either technically or scientifically minded?*
   A Yes
   B No
   C Uncertain

9. Would you describe yourself as either commercially or strategically minded?*
   A Yes
   B No
   C Uncertain

10. Would you describe yourself as risk-averse?*
    A Yes
    B No
    C Uncertain

11. Which information sources would you say you rely on most to anticipate likely future changes in your day-to-day life?*
    (Choose as many as you like)
    A Academic literature and publications
    B Advertising and marketing publications
    C Computer simulations
    D Conceptual models (e.g. thought experiments)
    E Financial publications
    F Government publications (i.e. leaflets)
    G Local society publications
    H National society publications
    I Newspapers (broadsheets)
    J Newspapers (tabloids)
    K Online news sites
    L Radio
    M Social media sites

N Stock markets
O TV programmes
P Word of mouth
Q Other

What are forecasts used for?

12. How important is it to you that the motivation of the person or organisation producing a forecast is clearly stated alongside the results produced?*

    e.g. Do you think that a clear statement of any personal influences (subjectivity) increases the credibility of the results and conclusions presented?

1	2	3	4	5

Not important		Fairly important		Very important

13. If predicted results demonstrate the original aim of the forecaster, does that (in your view) increase or negate the credibility of the forecast used?*

    e.g. If an organisation uses market forecasts to investigate the need for a new product, and then concludes that a new product is needed, does that give extra credibility to the original prediction or do you see this a self-fulfilling prophecy?

1	2	3	4	5

Reduces credibility		No effect		Increases credibility

14. If commercial ventures, which are based on forecast results, prove to be successful, does that increase the credibility of the forecast used?*

    e.g. If an organisation uses market forecasts to outline a business case for a new product, and then is successful with this new product in the marketplace, do you think the success demonstrates the accuracy of the original prediction, or do you think other factors may have played a more important role in the success?

1	2	3	4	5

Never		Occasionally		Very often

15. How important is it to you that a forecast can be extended to address other purposes outside of the original aim that it was intended for?*

e.g. If a weather forecast could also give you details of solar power generation levels, would this make the forecast more valuable in your view, or would this detract from the main purpose of the forecast?

1	2	3	4	5

Not important Fairly important Very important

16. How important is it for credibility that simulations tackle real-world problems as opposed to laboratory tests?*
    e.g. If a transport forecast uses simplified assumptions to predict traffic flows between cities (such as the assumption that the overall global population level does not change with time), would the results of this forecast still represent, in your view, a valid indication of the future?

1	2	3	4	5

Not important Fairly important Very important

17. How important is it to you that forecasts are targeted at a specific industry, domain, or condition (as opposed to a more generic prediction)?*
    e.g. Would you see a Bristol-based weather forecast as being more reliable than the BBC World Service weather forecast? (i.e. does a more specific context help to justify the predictions being made?)

1	2	3	4	5

Not important Fairly important Very important

Forecasting methods

18. How credible do you find it when analogies are used in research to support the outcome of forecasts?*
    e.g. If a city planning department uses observations of ant colonies and termite mounds to explore pedestrian movements and behaviours within city development concepts, do you think this is a valid analogy?

1	2	3	4	5

Never credible Occasionally credible Very credible

19. How convincing do you find the analogies commonly chosen in the media to explain the assumptions made and methods adopted in scientific research?*

    e.g. When scientific information is presented on the news, can you see how the analogies presented from natural events, biology, sociology, etc. matches the approaches taken by the researchers?

1	2	3	4	5
Not convincing		Occasionally convincing		Very convincing

20. How important do you find it to see the rationale behind the selected assessment criteria for future predictions?*

    e.g. If you are told that the main concern for a new technology in the future is its carbon dioxide emissions, (as opposed to the use of rare earth minerals to produce the technology, etc.), are you convinced that this is the main concern to focus on?

1	2	3	4	5
Not important		Fairly important		Very important

21. Do you feel that popular media and press predictions of the future generally use the right criteria to measure future changes?*

    e.g. Would a car magazine describing the energy needs of future electric vehicles in terms of 'miles per gallon' give you a clear impression of future energy consumption?

1	2	3	4	5
Never		Occasionally		Very often

22. If a forecast is shown to be the product of a collaborative effort does that increase your confidence in the results?*

    e.g. Do you think that group consultation would help to improve the realism of a market forecast compared to those developed in isolation?

1	2	3	4	5
Reduces confidence		No effect		Increases confidence

23. If there are sporadic gaps present in the data sets used to generate a forecast, do you still think it is possible to generate meaningful and helpful results?*

e.g. As exact migration numbers between countries are often not fully known, do you think migration forecasts are still meaningful? (i.e. do you think that missing information always presents a critical obstacle to producing helpful analysis?)

1	2	3	4	5
Never		Occasionally		Very often

24. How effective do you find sensitivity studies at improving your confidence in a simulation?*
   e.g. If published results from a transport forecast include analysis of the impact on predictions of varying key model parameters (such as national GDP and the price of oil) does this give you more confidence in the accuracy of forecasts produced?

1	2	3	4	5
Not effective		Moderately effective		Very effective

25. Do you think that the accuracy of predicted trends at a global (or macro) level is improved by forecasting patterns that emerge at a microscopic level?*
   e.g. Do you think that it would be possible to build up a more accurate picture of global weather patterns from combining all localised weather forecasts into a single model, or would this lead to increased errors in predictions? (i.e. would the 'sum of all parts' be equivalent to 'the whole', or would there be significant differences if you looked at forecasting on two different scales?)

1	2	3	4	5
Very unlikely		Unsure		Very likely

26. How many alternative methods do you think forecasts should be compared against to demonstrate sufficient credibility?*
   e.g. How many alternative climate models would you like to observe reproducing the same results as your own climate model to have confidence that your forecast of climate change was realistic?
   (Choose as many as you like)
   A 0 (no comparison necessary)
   B 1 to 4
   C 5 to 9
   D 10+
   E No fixed number (dependant on method being trialled)

27. How regularly do forecast results need to be compared against results obtained using alternative approaches to provide you with confidence that the prediction method used is still the most appropriate for the task?*

    e.g. If a population growth forecast based on current migration flows is generated every year, providing a 10 year prediction of a nations' changing demographics, how often do you think this annual forecast needs to be compared to growth projections based on future labour force estimates (or any other new approaches) to give you confidence that the migration flow approach is still the most appropriate method?

1	2	3	4	5
After several decades		After several years		Annually

28. How long should it take to gain an understanding of the modelling principles behind a forecast for the results produced to be considered easy to reproduce and verify in a commercial environment?*

    e.g. If it was possible to learn how an economic forecasting model works in a short period of time, would that suggest to you that methodological errors would be identified and resolved fast enough to make the technique commercially useful?

1	2	3	4	5
Order of months		Order of weeks		Order of days

Supporting information provided with forecasts

29. In your view, how important is comprehensively referenced background documentation (traceability) to the overall credibility of a forecast?*

    e.g. If an economic forecast presents plausible market results but does not provide sufficient references to explain the current market conditions and the types of forecasts that have been produced in the past, do you still find value in the conclusions?

1	2	3	4	5
Not important		Fairly important		Very important

30. How important do you think it is to see evidence of a rigorous methodology to provide confidence in the results of a forecast?*

    e.g. If a climate forecast suggests environmental changes that appear credible, but there is no clear indication of the logic behind the current predictions, then are the conclusions presented still worthwhile to you?

1	2	3	4	5

Not important Fairly important Very important

31. How important do you think it is to see evidence of well-defined model boundaries to provide confidence in the results of a forecast?*

    e.g. If an economic forecast suggests market changes that appear credible, but there is no clear indication of the limits of validity (i.e. conditions in which the model will not produce meaningful results), then are the conclusions presented still worthwhile to you? (for example, a forecast of European economic growth patterns may not be valid for Chinese markets where a different political and economic system exists)

1	2	3	4	5

Not important Fairly important Very important

32. How important do you think it is to see evidence of the iterative development of forecasting models to provide confidence in the results produced?*

    e.g. If an election forecast suggests political changes that appear credible, but there is no clear indication of how the forecasting model has evolved into its current form based on the results of previous elections, then are the conclusions presented as valuable to you?

1	2	3	4	5

Not important Fairly important Very important

33. How important do you think it is to see evidence that a range of different sources, opinions, and perspectives have been taken into account when generating forecasts to provide confidence in the results produced?*

    e.g. If a technology forecast suggests that new innovative technologies are likely to become commercially viable in the near future, but there is no clear indication of opinions provided by industry and technology experts, manufacturers, or members of the public being reviewed, then are the conclusions presented as valuable to you?

1	2	3	4	5

Not important Fairly important Very important

34. In your view, how important is complete traceability of all data sources to the overall credibility of a forecast?*

e.g. If a market forecast presents plausible results but does not provide the sources for all of the market data used, do you still find value in the conclusions?

1	2	3	4	5

Not important | Fairly important | Very important

35. How important do you think it is to see evidence of sensitivity studies being conducted on a model's initial conditions (i.e. the original state of the environment being modelled) to provide confidence in the final results of the forecast?*

    e.g. If a climate forecast presents significant changes resulting from one assumed average global temperature, but does not examine the effect of different starting temperatures, do you still find value in the conclusions?

1	2	3	4	5

Not important | Fairly important | Very important

36. In your view, how important is the demonstration of a rigorous software-checking process to the overall credibility of a computer-generated forecast?*

    e.g. If a population growth forecast presents plausible results but does not provide detailed evidence of checks carried out on the computer code used to run the simulation, do you still find value in the conclusions?

1	2	3	4	5

Not important | Fairly important | Very important

37. How effective do you find the inclusion of recommendations for future modelling developments in improving the credibility of forecasting techniques?*

    e.g. If a traffic forecast acknowledges current weaknesses in incorporating severe weather effects and outlines future refinements to improve this aspect of the simulation, does this give you confidence that the basic forecasting assumptions are sound and will ultimately lead to a reliable forecast?

1	2	3	4	5

Not effective | Moderately effective | Very effective

Using hindsight as a guide to foresight

38. In your view, does the examination of past scenarios give a good indication of uncertain future conditions?*
    i.e. How reliable do you find references to the past as an indication of the future?

1	2	3	4	5
Never		Occasionally		Very often

39. Do you need to see evidence of accurate forecasts being produced by existing applications of a given modelling technique before you are convinced of the method's viability?*
    i.e. Would you consider using a new forecasting technique in your day-to-day work without examples of the benefits demonstrated in other applications?

1	2	3	4	5
Never		Occasionally		Always

40. How accurately should a simulation be able to reproduce demonstrated results in order to provide you with confidence that future forecasts will also be useful?*
    e.g. If a product demonstrator is manufactured that provides real-life performance estimates of a new technology, how closely do you think a computer-generated simulation should be able to emulate these results to be considered useful?

1	2	3	4	5
"Ball park" accuracy is good enough		Close consistency is required		Exact numbers are required

41. Does the use of a historic test sample to calibrate models provide you with increased confidence that any forecasts produced by the model would accurately predict future disruptions?*
    e.g. Does the ability to reproduce historic patterns observed in financial markets give you increased confidence that an economic forecasting method will be accurate for predicting sudden market crashes in the future?

1	2	3	4	5
Reduces confidence		No effect		Increases confidence

42. How many historical scenarios should a forecast be compared against to demonstrate a high level of confidence in predicting disruptions?*

(Choose as many as you like)

A 0 (no correlation with the past)

B 1 to 4

C 5 to 9

D 10+

E No fixed number (dependant on environment being forecast)

43. How accurately should a forecasting model be able to reproduce historic trends in order to give you confidence that future predictions will be useful?*

    e.g. If a population forecast can approximate the changing global demographics over the past 20 years, and whether these populations are increasing or decreasing overall, is this accuracy sufficient (in your opinion) to use as a basis for future decisions on population-related environmental policies (such as legislation on resource consumption)?

1	2	3	4	5
"Ball park" accuracy is good enough		Close consistency is required		Exact numbers are required

Generating useful information

44. Is it more important for a long-term forecast to provide indicative general trends for future scenarios, or specific rankings of different possible outcomes?*

    e.g. If a technology forecast is produced to examine the possible evolutions of existing products over the next 20 years, is it necessary to be able to predict rankings of specific technologies against each other in order to make valuable investment decisions, or are general trends sufficient in this long-term timeframe?

1	2	3	4	5
General trends		Unsure		Specific probabilities

45. How extensively do the root causes of predicted events need to be known in order to provide you with a valuable insight into expected future changes?*

    e.g. How much certainty would you need of the root cause of predicted increases in natural gas prices in order to make a decision on how to heat your home in the future?

1	2	3	4	5

Causes do not need to be known		Causes should be estimated		Causes should be proven

46. How extensively do you feel you rely on pattern recognition to assess the credibility of a prediction?*
    e.g. If a weather forecast suggests the occurrence of familiar/recognisable pattern of weather at a particular time of year (such as summer storm fronts) does that suggest an increased likelihood of accuracy to you in model predictions?

1	2	3	4	5

Never		Occasionally		Very often

47. How important is it to you that forecasts are able to capture the appearance of previously undiscovered patterns or events?*
    e.g. If a market forecast identifies a new emerging phenomena (such as a previously unobserved type of consumer behaviour), does this increase the significance to you of the results being produced by this market forecast?

1	2	3	4	5

Not important		Fairly important		Very important

48. If new patterns are discovered within a forecast that cannot be easily explained using existing knowledge does this reduce your view of the credibility of the overall results?*
    e.g. If a new weather phenomena (such as El Nino) is predicted that cannot easily be traced back to known climate science, does the uncertainty associated with the predicted change in weather patterns decrease your confidence in the credibility of the original forecast?

1	2	3	4	5

Reduces confidence		No effect		Increases confidence

49. How confident are you generally in the ability of human judgement to filter out and eliminate 'background noise' from forecasts whilst preserving critical information?*
    e.g. When examining predictions of fluctuating financial markets, do you think humans are effective at correctly identifying the most important information to analyse, and subsequently the most important information to use for guiding investments?

1	2	3	4	5
Not confident		Moderately confident		Very confident

50. How confident are you generally in the ability of automated processes (i.e. computers) to filter out and eliminate 'background noise' from forecasts whilst preserving critical information?*
    e.g. When examining predictions of fluctuating financial markets, do you think computers are effective at correctly identifying the most important information to analyse, and subsequently the most important information to use for guiding investments?

1	2	3	4	5
Not confident		Moderately confident		Very confident

51. Computer simulations are now often used in disaster and emergency planning exercises. Do you believe that current virtual modelling techniques are sophisticated enough to be credible for realistic contingency planning in conditions that cannot be recreated in a laboratory environment?*
    e.g. In your opinion, could a computer model generate a reliable representation of a large-scale emergency for rapid decision and contingency planning purposes, that could not be tested otherwise?

1	2	3	4	5
Very unlikely		Unsure		Very likely

52. Do you think that the results of simulations play as important a role in guiding effective strategic decision-making as other information gathering approaches?*
    e.g. In your view would a computer-generated model of the introduction of a new product to market provide the necessary breadth and quality of information, compared to the results of a focus group analysis, to directly steer the outcome of commercial decisions?

1	2	3	4	5
Less important		Equally important		More important

Real-world behaviours

53. How important do you think it is to represent human factors in predictions of the future?*

e.g. If a transport forecast includes an assessment of the value of comfort to passengers, and the influence this has on their travel choices, do you think this will produce a more realistic prediction of future traffic levels?

1	2	3	4	5

Not important Fairly important Very important

54. In your opinion, can computer simulations provide a useful representation of human individuality?*
    e.g. If a city planning office uses computational behavioural models to predict pedestrian and vehicle movements through a new city development, do you think this will provide them with an improved understanding of how the constructed developments will actually be used?

1	2	3	4	5

Never Occasionally Very often

55. In your opinion, can computer simulations provide a useful representation of cultural and organisational behaviours?*
    e.g. If a market forecast uses computer-generated models to represent organisations and their commercial strategies, do you think this will provide an improved understanding of how and when real-life organisations will compete and collaborate?

1	2	3	4	5

Never Occasionally Very often

56. How important is it to you that simulations are able to identify the impact of changes beyond the main field of interest for the forecast?*
    e.g. If an energy forecast predicts that crude oil and natural gas sources will become scarcer in the future, leading to a rise in supply costs, and that this will have a direct impact on the economies of nations heavily dependent on oil and gas exports, does the identification of these 'knock-on effects' increase the usefulness for you of the original energy forecast?

1	2	3	4	5

Not important Fairly important Very important

57. If a forecasting technique can be shown to be useful for predicting multiple criteria of interest, does that increase your confidence that the results produced for the main area of focus are realistic?*

    e.g. If a transport forecast is used for predicting both traffic congestion levels and vehicle emissions, do you think that the traffic forecast is more likely to produce realistic results, or does this introduce additional uncertainty?

1	2	3	4	5

Reduces confidence — No effect — Increases confidence

58. The 'Butterfly Effect' describes the ability of tiny variations in environmental conditions to drastically change the outcome of large-scale events. Do you think that forecasts which include these local variations would provide a more valuable explanation of real-life chaotic behaviours?*

    e.g. Do you think that if a weather forecast was detailed enough to distinguish between very subtle environmental variations it would be able to accurately identify the causes of extreme weather events (that may otherwise have been undetected), or would this only introduce additional uncertainty?

1	2	3	4	5

Very unlikely — Unsure — Very likely

Forecasting disruptions

59. If a disruptive event is predicted in the future, does having knowledge of the likely extent and localisation of the impact provide you with increased confidence that the disruption is likely to occur?*

    e.g. If an economic forecast provides details of the businesses that would be most affected by a potential market crash, and the depth of the market impact, does this increase the probability, in your opinion, that the forecast disruption is realistic?

1	2	3	4	5

Reduces confidence — No effect — Increases confidence

60. When a disruptive event occurs, do you think it is more important to accurately forecast the magnitude of the disruption or the time taken to adjust to the changes made?*

    e.g. If a technology forecast predicts that an emerging technology (such as 3D printing) will soon revolutionise a wide range of industries, do you think it is more important from a commercial point of view to understand the scale of the changes that will be made, or the time that will be required for the changes to be implemented?

1	2	3	4	5

The magnitude of the disruption — Equally important — The time taken to adjust

61. Do you think that by mapping the propagation of disruptive events beyond their initial field of origin the realism of current forecasting techniques would be improved?*
    e.g. If an air traffic forecast identifies the spill-over effects from the sudden closure of a major airport on to the road and railway networks, does this increase the realism of the traffic forecast, or does this only introduce additional uncertainty?

1	2	3	4	5

Very unlikely — Unsure — Very likely

That's the last question! Thank you for taking part in this survey, and providing an insight into your views on forecasting future disruptions. You can now submit your results on the next screen.

Appendix C - Preprocessing scripts for MATLAB

Listing 1: batch_html_conversion.m

```
% This script loops through the 'htmlTableToCell.m' script in order to
% quickly convert and save a batch of Orbit patent data files (saved as
% html tables) into .MAT files

clearvars
clear all
close all

tic()

% Request the user to choose the current working directory (NB: if no
% folder is selected in the user interface then the current working
% directory is taken to be the filepath) OR do not ask the user and just
% take the current directory:
% filepath = uigetdir;
filepath = pwd;

% Identify the name of the selected working directory:
[upperPath,deepestFolder] = fileparts(filepath);

% Identify html files in the selected working directory that match the name
% of the folder:
files = dir('*.html');

% Use first column header to identify the start of the table:
table.idTableBy.plaintextInFirstTD = 'Family Accession Nbr';

% Iterate through input .html files in the current folder directory:
for i = 1:numel(files)
% for i = 6:numel(files)
% for i = 1:3
    % Reset cell array:
```

```
    clearvars cell_array

    % Select the next html file to convert:
    name = files(i).name;

    % Identify the record numbers included in each html file (NB: '(\d*)'
    % selects any number of digits at this point in the string):
    batch_limits = regexp(name,strcat(deepestFolder,' patents \(Orbit
       search results (\d*) - (\d*)\).html'),'tokens');

    % Construct the variable name for this specific cell array:
    cell_array_name = [strrep(lower(deepestFolder),' ','_'),'_patents_',
       batch_limits{1,1}{1,1},'_',batch_limits{1,1}{1,2}];

    % Call the 'htmlTableToCell.m' script for the current html file:
    cell_array = htmlTableToCell(name,table);

    % Save the current cell array to a .MAT file:
%     savefile = [deepestFolder,' patent data ',batch_limits{1,1}{1,1},' -
   ',batch_limits{1,1}{1,2},' test','.mat'];
    savefile = [deepestFolder,' patent data ',batch_limits{1,1}{1,1},' - ',
       batch_limits{1,1}{1,2},' ',date,'.mat'];
    save(savefile,'cell_array');

    toc()
end

toc()
```

Listing 2: extract_patent_metrics.m

```
% This script is used to clean patent data files (already imported from
% HTML files using the 'batch_html_conversion.m' script and saved as .MAT
% files) and extract patent metrics required for use in subsequent 'nearest
% neighbour' pattern recognition analysis.

clearvars
clear all
close all

tic()

% Request the user to choose the current working directory (NB: if no
% folder is selected in the user interface then the current working
% directory is taken to be the filepath) OR do not ask the user and just
% take the current directory:
% filepath = uigetdir;
filepath = pwd;

% Identify the name of the selected working directory:
[upperPath,deepestFolder] = fileparts(filepath);

% Identify .MAT files in the selected working directory that match the name
% of the folder:
files = dir(strcat(deepestFolder,'*.mat'));

% Load list of International Patent Classification (IPC) subclasses:
load('IPC_subclasses.mat','IPC_subclasses')

% Initialise upper and lower global time limits:
upper_time_limit = inf;
lower_time_limit = -inf;

% Initialise the 'completed files' tracker:
completed_files = zeros(size(files,1),1);

% Preallocate empty cell arrays for building cumulative lists of unique
% corporate, non-corporate, and set of inventor entries:
unique_corporations_cumulative = cell(1,size(files,1));
unique_non_corporates_cumulative = cell(1,size(files,1));
unique_set_of_inventors_cumulative = cell(1,size(files,1));

% Preallocate empty cell arrays for compiling file summary counts:
patents_by_application_year = cell(1,size(files,1));
patents_by_priority_year = cell(1,size(files,1));
corporates_by_priority_year = cell(1,size(files,1));
```

```
non_corporates_by_priority_year = cell(1,size(files,1));
set_of_inventors_by_priority_year = cell(1,size(files,1));
cited_references_by_priority_year = cell(1,size(files,1));
cited_patents_by_priority_year = cell(1,size(files,1));
IPC_subclass_frequency_by_priority_year = cell(1,size(files,1));
distinct_IPC_subclass_by_priority_year = cell(1,size(files,1));
top_5_IPC_subclass_patents_by_priority_year = cell(1,size(files,1));
top_10_IPC_subclass_patents_by_priority_year = cell(1,size(files,1));

% Create array of table names:
table_names = {'patents_by_application_year';'patents_by_priority_year';...
    'corporates_by_priority_year';'non_corporates_by_priority_year';...
    'set_of_inventors_by_priority_year';'cited_references_by_priority_year';...
    'cited_patents_by_priority_year';'distinct_IPC_subclass_by_priority_year';...
    'top_5_IPC_subclass_patents_by_priority_year';'top_10_IPC_subclass_patents_by_priority_year'};

%% Iterate through input .MAT files in the current folder directory:
for file_ID = 1:numel(files)
% for file_ID = 2:4
% for file_ID = 2:2
% for file_ID = 16:16
% for file_ID = 22:22
    % Select the next .MAT file to convert:
    name = files(file_ID).name;

    % Load .MAT file containing patent data:
    load(name, 'cell_array')

    % Select cell array containing the patent data to evaluate:
    data_set = 'cell_array';

    % Create table object from cell array data set:
    data_table = cell2table(eval(strcat(data_set, '(2:end,:)')));

    % Replace any ' ' values with a blank table cell:
    data_table = standardizeMissing(data_table,' ');

    % Determine the number of rows in the data table (not including
    % headers):
    rows = size(data_table,1);

    % Read in table headings as stored in cell array:
    headings = eval(strcat(data_set, '(1,:)'));
```

```
% Remove any leading and trailing white spaces from headings:
headings = strtrim(headings);

% Remove or replace any remaining white spaces, slashes, brackets, full
% stops, or hyphens in headings with underscores:
headings = strrep(headings,' ','_');
headings = strrep(headings,'/','_');
headings = strrep(headings,'(','');
headings = strrep(headings,')','');
headings = strrep(headings,'.','');
headings = strrep(headings,'-','_');

% Identify headings that are unique (in the same order that they
% currently appear in):
[~,unique_headings_index,~] = unique(headings,'stable');
unique_headings = ismember(1:size(headings,2),unique_headings_index);

for i = 1:size(headings,2)
    if unique_headings(i) == 0
        headings(i) = strcat(headings(i),'_',num2str(i));
    end
end

% Assign headings to table variables:
data_table.Properties.VariableNames = headings;

% Add pivot table counter column to table:
data_table.Pivot_Table_Counter = ones(rows,1);

% Identify valid date entries:
missing_dates = strcmp(data_table.Date,'0');
missing_dates_index = find(missing_dates == 1);
valid_dates = ~missing_dates;

% Extract 'Basic Year' for each patent family:
data_table.Basic_Year(valid_dates,1) = year(data_table.Date(valid_dates
    ));

% Convert required cell arrays into character arrays:
current_assignee_name = char(data_table.
    Current_Applicant__or_Assignee_Name);
family_normalized_assignee_name = char(data_table.
    Family_Normalized_Assignee_name);
set_of_inventors = char(data_table.Inventor);
```

```
% Define string truncation limits:
char_limit_1 = 12;
char_limit_2 = 13;

% Preallocate empty arrays and tables for derived metrics:
application_date = cell(rows,2);
cited_references = zeros(rows,1);
cited_patents = zeros(rows,1);
matched_IPC_subclasses = array2table(zeros(rows,size(IPC_subclasses,1))
    ,'VariableNames', IPC_subclasses);

% Truncate data entries in 'Current Applicant or Assignee Name',
% 'Family Normalized Assignee name', and 'Inventor' columns in order to
% improve identification of unique entries:
truncated_current_assignee_name = cellstr(current_assignee_name(:,1:
    char_limit_1));
truncated_family_normalized_assignee_name = cellstr(
    family_normalized_assignee_name(:,1:char_limit_2));
truncated_set_of_inventors = cellstr(set_of_inventors(:,1:char_limit_1)
    );

% Assign unique corporation ID to companies appearing in truncated sets
% of data:
if sum(completed_files) == 0
     unique_corporations_cumulative{file_ID} = unique(
         truncated_family_normalized_assignee_name);
     unique_corporations = unique_corporations_cumulative{file_ID};
else
     new_unique_corporations = unique(
         truncated_family_normalized_assignee_name);
     new_unique_corporations_idx = find(~ismember(
         new_unique_corporations,unique_corporations));
     unique_corporations_cumulative{file_ID} = new_unique_corporations(
         new_unique_corporations_idx);
     unique_corporations = [unique_corporations;
         unique_corporations_cumulative{file_ID}];
end
[~,data_table.Corporation_ID] = ismember(
    truncated_family_normalized_assignee_name(:,1),unique_corporations);

% Assign unique non-corporate ID to patents that are not associated
% with a recognised company name appearing in the truncated sets of
% data:
non_corporates_idx = find(strcmp(
    truncated_family_normalized_assignee_name,'') == 1);
non_corporates = truncated_current_assignee_name(non_corporates_idx);
```

```
    if sum(completed_files) == 0
        unique_non_corporates_cumulative{file_ID} = unique(non_corporates);
        unique_non_corporates = unique_non_corporates_cumulative{file_ID};
    else
        new_unique_non_corporates = unique(non_corporates);
        new_unique_non_corporates_idx = find(~ismember(
            new_unique_non_corporates,unique_non_corporates));
        unique_non_corporates_cumulative{file_ID} =
            new_unique_non_corporates(new_unique_non_corporates_idx);
        unique_non_corporates = [unique_non_corporates;
            unique_non_corporates_cumulative{file_ID}];
    end
    [~,data_table.Non_Corporates_ID] = ismember(
       truncated_current_assignee_name(:,1),unique_non_corporates);

    % Assign unique set-of-inventors ID to groups of inventors appearing in
    % truncated sets of data:
    if sum(completed_files) == 0
        unique_set_of_inventors_cumulative{file_ID} = unique(
            truncated_set_of_inventors);
        unique_set_of_inventors = unique_set_of_inventors_cumulative{
            file_ID};
    else
        new_unique_set_of_inventors = unique(truncated_set_of_inventors);
        new_unique_set_of_inventors_idx = find(~ismember(
            new_unique_set_of_inventors,unique_set_of_inventors));
        unique_set_of_inventors_cumulative{file_ID} =
            new_unique_set_of_inventors(new_unique_set_of_inventors_idx);
        unique_set_of_inventors = [unique_set_of_inventors;
            unique_set_of_inventors_cumulative{file_ID}];
    end
    [~,data_table.Set_of_Inventors_ID] = ismember(
       truncated_set_of_inventors(:,1),unique_set_of_inventors);

    % Iterate through patent family records to extract specific patent
    % indicators which may have multiple values stored for the same record:
    for i = 1:rows
        % Extract the application date for each patent family:
        delimited_application_data = strsplit(char(data_table.
            Application_Data(i)));
        application_date(i,1) = delimited_application_data(2);
        if (strcmp(application_date(i,1), '0') == 1) || (sum(isletter(char(
            application_date(i,1)))) ~= 0)
             try
                 possible_application_year = char(delimited_application_data
                     (3));
```

```
                try
                    application_date{i,2} = possible_application_year(2:5);
                catch
                    application_date{i,2} = '0';
                end
            catch
                application_date{i,2} = '0';
            end

        end

        % Extract the priority dates for each patent family:
        delimited_priority_details = strsplit(char(data_table.
            Priority_Details(i)));

        % Reset and preallocate priority year array for each patent family:
        priority_year_set = zeros(1,size(delimited_priority_details,2));

        % Scan through delimited priority details to identify earliest
        % priority date:
        for j = 1:size(delimited_priority_details,2)
            try
                priority_year_set(j) = year(delimited_priority_details(j));
            catch
                priority_year_set(j) = NaN;
            end
        end

        % Identify the earliest 'Priority Year' from the priority year set
        % for each patent family:
        data_table.Priority_Year(i,1) = min(priority_year_set);

        % Count the number of references cited for each patent family:
        if strcmp(data_table.References(i),'') == 0
            cited_references(i) = size(strfind(char(data_table.References(i
                )),'<br /><br />'),2);
        else
            cited_references(i) = 0;
        end

        % Count the number of patents cited for each patent family:
        if strcmp(data_table.Cited_Patents(i),'') == 0
            cited_patents(i) = size(strfind(char(data_table.Cited_Patents(i
                )),'<br /><br />'),2);
        else
            cited_patents(i) = 0;
```

```
        end

        % Extract the distinct IPC subclasses associated with each patent
        % family:
        delimited_IPC_subclasses = char(strsplit(char(data_table.
            Current_IPC(i)),'<br /><br />'));
        % Set table row to zero if no IPC details are provided:
        if isempty(delimited_IPC_subclasses)
            matched_IPC_subclasses(i,:) = array2table(zeros(1,size(
                IPC_subclasses,1)));
        else
            % Truncate IPC codes to only the first four digits (subclasses)
            % and identify the distinct subclasses referenced by the
            % current patent family:
            truncated_IPC_subclasses = cellstr(delimited_IPC_subclasses
                (:,1:4));
            unique_IPC_subclasses = unique(truncated_IPC_subclasses);

            % Identify indexes of matched IPC subclasses:
            [~,matched_IPC_subclasses_idx] = ismember(unique_IPC_subclasses
                ,IPC_subclasses);

            % Set corresponding IPC subclass count values to 1:
            try
                matched_IPC_subclasses(i,matched_IPC_subclasses_idx) =
                    array2table(1);
            catch
                % No IPC subclass matches found for this patent family
                % (probably as a result of a typo in the recorded
                % 'Current_IPC' value)
            end
        end
    end

    % Identify valid application date entries:
    missing_application_dates = strcmp(application_date(:,1),'0') + ~
        cellfun(@isempty,application_date(:,2));
    missing_application_dates_index = find(missing_application_dates ~= 0);
    valid_application_dates = ~missing_application_dates;

    % Replace any empty alternative application dates with '0' (so that all
    % values are classed as strings):
    empty_alt_application_dates = cellfun('isempty',application_date(:,2));
    application_date(empty_alt_application_dates,2) = {'0'};

    % Extract the 'Application Year' from the application date:
```

```
data_table.Application_Year(valid_application_dates,1) = year(application_date(valid_application_dates));

% Identify missing 'Priority Year' entries:
missing_Priority_Year_index = find(isnan(data_table.Priority_Year) == 1);

% Replace missing 'Priority Year' values with minimum (non-zero where
% possible) of 'Application Year' and 'Basic Year' values:
alternative_year_values = [data_table.Basic_Year(missing_Priority_Year_index,1) data_table.Application_Year(missing_Priority_Year_index,1) cellfun(@str2num, application_date(missing_Priority_Year_index,2))];
alternative_year_values(alternative_year_values == 0) = inf;
earliest_alternative_year = min(min(alternative_year_values(:,1), alternative_year_values(:,2)),alternative_year_values(:,3));
earliest_alternative_year(earliest_alternative_year == inf) = 0;
data_table.Priority_Year(missing_Priority_Year_index,1) = earliest_alternative_year;

% Identify any still outstanding 'Priority Year' values:
still_missing_Priority_Year_index = find(data_table.Priority_Year == 0);

% Replace missing 'Application Year' values with 'Priority Year'
% values:
data_table.Application_Year(missing_application_dates_index,1) = data_table.Priority_Year(missing_application_dates_index,1);

% Initialise the year counter for the timeframe considered in the
% patent data set (the earliest known US patent is from 1790
% [https://en.wikipedia.org/wiki/History_of_patent_law] - removing any
% years earlier than 1790 will also remove some entries where typos,
% etc. have given incorrect data entries):
time_period = (min(min(data_table.Priority_Year(data_table.Priority_Year >= 1790)),...
    min(data_table.Application_Year(data_table.Application_Year >= 1790))):...
    max(max(data_table.Priority_Year(data_table.Priority_Year <= 2020)),...
    max(data_table.Application_Year(data_table.Application_Year <= 2020))))';

% Check if the time period considered in the current file is outside of
% the existing time limits established from previous files, and update
% global time limits as necessary:
```

```
if upper_time_limit == inf
    upper_time_limit = max(time_period);
elseif max(time_period) > upper_time_limit
    upper_time_limit = max(time_period);
end
if lower_time_limit == -inf
    lower_time_limit = min(time_period);
elseif min(time_period) < lower_time_limit
    lower_time_limit = min(time_period);
end

% Preallocate empty arrays for derived metrics:
corporates_by_priority_year_values = zeros(size(time_period,1),1);
non_corporates_by_priority_year_values = zeros(size(time_period,1),1);
set_of_inventors_by_priority_year_values = zeros(size(time_period,1),1)
   ;
cited_references_by_priority_year_values = zeros(size(time_period,1),1)
   ;
cited_patents_by_priority_year_values = zeros(size(time_period,1),1);
IPC_subclass_frequency_by_priority_year_values = zeros(size(time_period
   ,1),size(IPC_subclasses,1));
distinct_IPC_subclass_by_priority_year_values = zeros(size(time_period
   ,1),1);
top_5_IPC_subclass_patents_by_priority_year_values = zeros(size(
   time_period,1),1);
top_10_IPC_subclass_patents_by_priority_year_values = zeros(size(
   time_period,1),1);

% Cycle through timeframe considered in patents to calculate yearly
% totals:
for i = 1:(max(time_period) - min(time_period))
    % Identify the indices of patent families recorded in the current
    % priority year of interest:
    idx = find(data_table.Priority_Year == time_period(i));

    % Count the number of unique corporate IDs associated with patents
    % in any given year (and remove blanks which have ID '1'):
    unique_corp_ID_by_year = unique(data_table.Corporation_ID(idx));
    unique_corp_ID_by_year_no_blanks = unique_corp_ID_by_year(
       unique_corp_ID_by_year ~= 1);
    corporates_by_priority_year_values(i) = size(
       unique_corp_ID_by_year_no_blanks,1);

    % Count the number of unique non-corporate IDs associated with
    % patents in any given year (and remove blanks which have ID '1',
    % and corporations which have ID '0'):
```

```
        unique_non_corp_ID_by_year = unique(data_table.Non_Corporates_ID(
            idx));
        unique_non_corp_ID_by_year_no_blanks = unique_non_corp_ID_by_year((
            unique_non_corp_ID_by_year ~= 0) & (unique_non_corp_ID_by_year
            ~= 1));
        non_corporates_by_priority_year_values(i) = size(
            unique_non_corp_ID_by_year_no_blanks,1);

        % Count the number of unique set of inventors IDs associated with
        % patents in any given year (and remove blanks which have ID '1'):
        unique_set_of_inventors_ID_by_year = unique(data_table.
            Set_of_Inventors_ID(idx));
        unique_set_of_inventors_ID_by_year_no_blanks =
            unique_set_of_inventors_ID_by_year(
            unique_set_of_inventors_ID_by_year ~= 1);
        set_of_inventors_by_priority_year_values(i) = size(
            unique_set_of_inventors_ID_by_year_no_blanks,1);

        % Count the total number of cited references associated with
        % patents in any given year:
        cited_references_by_priority_year_values(i) = sum(cited_references(
            idx));

        % Count the total number of cited patents associated with patents
        % in any given year:
        cited_patents_by_priority_year_values(i) = sum(cited_patents(idx));

        % Count the frequency of IPC subclasses being associated with
        % patents in any given year:
        IPC_subclass_frequency_by_priority_year_values(i,:) = sum(
            table2array(matched_IPC_subclasses(idx,:)),1);

        % Count the number of distinct IPC subclasses that are recorded as
        % being associated with patents in any given year:
        distinct_IPC_subclass_by_priority_year_values(i) = sum(
            IPC_subclass_frequency_by_priority_year_values(i,:) ~= 0);

        % Rank the IPC subclasses according to the number of associated
        % patent families for any given year:
        [max_IPC_subclass_counts,max_IPC_subclass_counts_idx] = sort(
            IPC_subclass_frequency_by_priority_year_values(i,:),'descend');

        % Extract the aggregate count of the number of patent families
        % associated with the top 5 and top 10 IPC subclasses for any given
        % year:
```

```
            top_5_IPC_subclass_patents_by_priority_year_values(i) = sum(max_IPC_subclass_counts(1:5));
            top_10_IPC_subclass_patents_by_priority_year_values(i) = sum(max_IPC_subclass_counts(1:10));
        end

    % Build pivot and summary tables:
    patents_by_application_year{file_ID} = pivot_table(data_table,'Application_Year','Pivot_Table_Counter',@sum);
    patents_by_priority_year{file_ID} = pivot_table(data_table,'Priority_Year','Pivot_Table_Counter',@sum);
    corporates_by_priority_year{file_ID} = table(time_period,corporates_by_priority_year_values);
    non_corporates_by_priority_year{file_ID} = table(time_period,non_corporates_by_priority_year_values);
    set_of_inventors_by_priority_year{file_ID} = table(time_period,set_of_inventors_by_priority_year_values);
    cited_references_by_priority_year{file_ID} = table(time_period,cited_references_by_priority_year_values);
    cited_patents_by_priority_year{file_ID} = table(time_period,cited_patents_by_priority_year_values);
    IPC_subclass_frequency_by_priority_year{file_ID} = [table(time_period) array2table(IPC_subclass_frequency_by_priority_year_values, 'VariableNames', IPC_subclasses)];
    distinct_IPC_subclass_by_priority_year{file_ID} = table(time_period,distinct_IPC_subclass_by_priority_year_values);
    top_5_IPC_subclass_patents_by_priority_year{file_ID} = table(time_period,top_5_IPC_subclass_patents_by_priority_year_values);
    top_10_IPC_subclass_patents_by_priority_year{file_ID} = table(time_period,top_10_IPC_subclass_patents_by_priority_year_values);

    % Append the current file ID to the 'completed files' tracker:
    completed_files(file_ID) = 1;

    toc()
end

% Identify indices of completed files:
completed_files_idx = find(completed_files ~= 0);

% Build global time period table:
global_time_period = (lower_time_limit:upper_time_limit)';

%% Create structure containing nested output tables:
summary_tables = struct('Names',table_names','Tables',{
    patents_by_application_year,patents_by_priority_year,...
```

```
    corporates_by_priority_year,non_corporates_by_priority_year,...
    set_of_inventors_by_priority_year,cited_references_by_priority_year,...
    cited_patents_by_priority_year,distinct_IPC_subclass_by_priority_year,...
    top_5_IPC_subclass_patents_by_priority_year,top_10_IPC_subclass_patents_by_priority_year},...
    'Final_Tables',cell(1,numel(table_names)));

for i = 1:sum(completed_files)
    % Select completed file ID:
    file_ID = completed_files_idx(i);

    % Iterate through summary tables corresponding to each completed file:
    for j = 1:numel(table_names)
        % Expand summary tables as necessary to include years with zero
        % records:
        missing_years_idx = ~ismember(global_time_period,table2array(summary_tables(j).Tables{1,file_ID}(:,1)));
        missing_years = missing_years_idx .* global_time_period;
        missing_years = missing_years(missing_years ~= 0);
        missing_entries = array2table([missing_years zeros(size(missing_years,1),1)],'VariableNames',eval(strcat(table_names{j},'{file_ID}.Properties.VariableNames')));
        current_table = sortrows([summary_tables(j).Tables{1,file_ID};missing_entries]);

        % Remove any years earlier than 1790 (which will also remove some
        % entries where typos, etc. have given incorrect data entries, such
        % as 'zero year' summary counts from tables):
        toDelete = logical((table2array(current_table(:,1)) < 1790) + (table2array(current_table(:,1)) > 2020));
        current_table(toDelete,:) = [];
        summary_tables(j).Tables{1,file_ID} = current_table;
    end
end

% Combine summary tables into one overall patent indicator matrix:
for j = 1:numel(table_names)
    % Initialise or reset cumulative count for each table type:
    cumulative_count = zeros(size(global_time_period,1),sum(completed_files));

    % Append counts in completed tables into one summary vector for the
    % current table type:
    for i = 1:sum(completed_files)
        % Select completed file ID:
```

```
        file_ID = completed_files_idx(i);

        % Populate cumulative count array with the summary results from
        % each file:
        cumulative_count(:,i) = table2array(summary_tables(j).Tables{1,
            file_ID}(:,2));
    end

    % Sum cumulative file counts to get the overall count:
    overall_count = sum(cumulative_count,2);

    % Send overall count back to summary tables:
    summary_tables(j).Final_Tables = [global_time_period overall_count];
end

% Save the current cell array to a .MAT file in the current working
% directory:
savefile = 'Summary development trends from patent data.mat';
save(savefile,'summary_tables');

% Determine screensize so that figures are scaled to the right size for the
% current monitor (scrsz == screen size vector [left, bottom, width,
% height])
scrsz = get(0,'ScreenSize');

% Generate a new figure showing the development trends of all patent
% indicators considered:
figure('Name',['Development trends of patent indicators for ',lower(
    deepestFolder)],'NumberTitle','off','OuterPosition', [1, 1, scrsz(3),
    scrsz(4)]);
hold on

% Plot all patent indicators on the same figure:
for j = 1:numel(table_names)
    plot(summary_tables(j).Final_Tables(:,1),summary_tables(j).Final_Tables
        (:,2))
end

% Set figure title, x-axis, and y-axis labels:
title(['Development trends of patent indicators for ',lower(deepestFolder)
    ],'FontSize',14);
xlabel('Year','FontSize',12);
ylabel('Count','FontSize',12);

% Add legend to figure for development trends:
legend(strrep(table_names,'_',' '),'FontSize',12,'Location','northwest');
```

```
% Save the current figure to a .FIG file in the current working directory:
savefig(['Development trends of patent indicators for ',lower(deepestFolder
    ),'.fig'])

toc()
```

Appendix D - Analysis scripts for MATLAB

Listing 3: match_TLC_stages.m

```
% This script is used to match the development progress of chosen test
% technologies against the concept of the technology life cycle (TLC)
% presented by Arthur [A.D. Little, The strategic management of technology,
% European Management Forum, Davos, 1981] to measure technological changes.
% The methodology used in this script is taken from 'Technology life cycle
% analysis method based on patent documents' [L. Gao, A.L. Porter, J. Wang,
% S. Fang, X. Zhang, T. Ma, W. Wang, L. Huang, 'Technology life cycle
% analysis method based on patent documents', Technological Forecasting &
% Social Change, 2013]

clearvars
clear all
close all

tic()

% Request the user to choose the current working directory (NB: if no
% folder is selected in the user interface then the current working
% directory is taken to be the filepath) OR do not ask the user and just
% take the current directory:
% filepath = uigetdir;
filepath = pwd;

% Identify the name of the selected working directory:
[patent_data_path,deepestFolder] = fileparts(filepath);

% Create empty structure for storing technology names, filepaths, datasets
% (i.e. summary count tables), and TLC stage labels:
training_data = struct('Technology',[],'Filepath',[],'Counts',[],'
    TLC_stages',[],'Label_set',[],'Points',[],'Transformed_Array',[],'
    Smoothed_Array',[],'Trimmed_Array',[],'Normalised_Array',[]);
```

```
test_data = struct('Technology',[],'Filepath',[],'Counts',[],'TLC_stages',[],'Label_set',[],'Points',[],'Transformed_Array',[],'Smoothed_Array',[],'Trimmed_Array',[],'Normalised_Array',[]);

% Specify the training technologies to use in 'nearest neighbour'
% classification process:
training_technologies(1).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','TFT-LCD','Wind energy','Wireless data transfer'};
training_technologies(2).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(3).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(4).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Wind energy','Wireless data transfer'};
training_technologies(5).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','Wireless data transfer'};
training_technologies(6).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(7).included_sets = {'CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(8).included_sets = {'CRT','Ink Jet printers','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(9).included_sets = {'CRT','Ink Jet printers','Nuclear energy','Solar PV','Wireless data transfer'};
% Combinations using inverse hyperbolic sine transforms:
training_technologies(11).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','TFT-LCD','Wind energy','Wireless data transfer'};
training_technologies(12).included_sets = {'Compact Fluorescent Lamps','CRT','Ink Jet printers','LED lights','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(18).included_sets = {'CRT','Ink Jet printers','Nuclear energy','Solar PV','Wind energy','Wireless data transfer'};
training_technologies(19).included_sets = {'CRT','Ink Jet printers','Nuclear energy','Solar PV','Wireless data transfer'};
% NB: The Technology Life Cycle stages given in 'Technology life cycle
% analysis method based on patent documents' match well to those quoted in
% 'UKERC Technology and Policy Assessment: Innovation timelines from
% invention to maturity' (see 'Innovation Timescales - Working paper -
```

```matlab
% March 2016.pdf')
% NB: Wireless data transfer is assumed to be equivalent to 'Mobile Phones'
% in 'UKERC Technology and Policy Assessment: Innovation timelines from
% invention to maturity' (see explanatory notes in 'Technology adoption
% data notes.txt')
% NB: Ink-jet printers is based on Fig. 1 in 'A new approach for
% understanding dominant design: The case of the ink-jet printer'

% Select the training technology combination to use in this analysis:
selected_training_datasets = 12;

for i = 1:numel(training_technologies(selected_training_datasets).
    included_sets)
     training_data(i).Technology = training_technologies(
         selected_training_datasets).included_sets(i);
end

%% Move to the patent data working directory:
cd(patent_data_path)

%% Select or build the path directories to the training technology datasets
     and load the training data:
for i = 1:numel(training_data)
    % training_data(i).Filepath = uigetdir;
    training_data(i).Filepath = [patent_data_path,'\',char(training_data(i)
        .Technology)];

    % Change directory to the directory of the current training dataset:
    cd(training_data(i).Filepath)

    % Load the summary tables for the current training technology:
    training_data(i).Counts = load('Summary development trends from patent
        data.mat','summary_tables');

    % Load the Technology Life Cycle stage labels associated with the
    % development of the current training technology:
    training_data(i).TLC_stages = load('Technology Life Cycle stage labels.
        mat','TLC_stages');

    % Construct training points matrix for the current training dataset:
    training_data(i).Points(:,1) = training_data(i).Counts.summary_tables
        (1).Final_Tables(:,1);
    training_data(i).Transformed_Array(:,1) = training_data(i).Counts.
        summary_tables(1).Final_Tables(:,1);
    training_data(i).Smoothed_Array(:,1) = training_data(i).Counts.
        summary_tables(1).Final_Tables(:,1);
```

```
    training_data(i).Trimmed_Array(:,1) = training_data(i).Counts.
        summary_tables(1).Final_Tables(:,1);
    training_data(i).Normalised_Array(:,1) = training_data(i).Counts.
        summary_tables(1).Final_Tables(:,1);
    for j = 1:numel(training_data(i).Counts.summary_tables)
        training_data(i).Points(:,j+1) = training_data(i).Counts.
            summary_tables(j).Final_Tables(:,2);
        current_array = training_data(i).Points(:,j+1);

        % Transform the training data points by calculating the equivalent
        % Inverse Hyperbolic Sine values (this in itself is approximately
        % equivalent to calculating the natural logarithm of the values,
        % except that this can also handle data values equal to zero):
        training_data(i).Transformed_Array(:,j+1) = asinh(current_array);

        % Smooth the training data points by calculating three-year moving
        % averages for each of the patent indicators considered:
%           training_data(i).Smoothed_Array(:,j+1) = smooth(current_array,3);
        training_data(i).Smoothed_Array(:,j+1) = smooth(training_data(i).
            Transformed_Array(:,j+1),3);
    end

    % Trim the array to remove the last few years were records have not yet
    % all been accounted for (i.e. it normally takes several years to
    % register all the patent records from a specific year, so the very end
    % years are likely to be incomplete). In these datasets, data after
    % 2011 seems to tail-off:
    trim_index = find(training_data(i).Smoothed_Array(:,1) > 2011);
    training_data(i).Trimmed_Array = training_data(i).Smoothed_Array;
    training_data(i).Trimmed_Array(trim_index,:) = [];
    training_data(i).Normalised_Array(trim_index,:) = [];

    % Construct normalised training points matrix for the current training
    % dataset:
    for j = 1:numel(training_data(i).Counts.summary_tables)
        % Normalise the training data points by dividing all values by the
        % maximum recorded value for each of the patent indicators
        % considered:
        training_data(i).Normalised_Array(:,j+1) = training_data(i).
            Trimmed_Array(:,j+1) / max(training_data(i).Trimmed_Array(:,j+1)
            );
    end

    % Extract the trimmed label set for the current training set:
```

```
    training_data(i).Label_set(:,1) = training_data(i).TLC_stages.
       TLC_stages.Year(ismember(training_data(i).TLC_stages.TLC_stages.Year
       ,training_data(i).Normalised_Array(:,1)));
    training_data(i).Label_set(:,2) = training_data(i).TLC_stages.
       TLC_stages.TLC_stage(ismember(training_data(i).TLC_stages.TLC_stages
       .Year,training_data(i).Normalised_Array(:,1)));

    % Extend trimmed label set if necessary to ensure the number of points
    % in the label set matches the number of points in the training
    % dataset (set any previously undefined TLC label points to 0 OR 1):
    label_set_extension_years = training_data(i).Normalised_Array(~ismember
       (training_data(i).Normalised_Array(:,1),training_data(i).TLC_stages.
       TLC_stages.Year),1);
    if ~isempty(label_set_extension_years)
%         label_set_extension = [label_set_extension_years, zeros(size(
   label_set_extension_years,1),1)];
        label_set_extension = [label_set_extension_years, ones(size(
           label_set_extension_years,1),1)];
        training_data(i).Label_set = sortrows([training_data(i).Label_set;
           label_set_extension]);
    end

    % Return to the patent data working directory:
    cd(patent_data_path)
end

%% Change directory back to original file path:
cd(filepath)

% Load the test technology dataset into the empty test data structure:
test_data.Filepath = filepath;

% Load the summary tables for the test technology:
test_data.Counts = load('Summary development trends from patent data.mat','
   summary_tables');

%% Check that training data and test data are using the same number of
   patent indicators:
if numel(test_data.Counts.summary_tables) ~= numel(training_data(1).Counts.
   summary_tables)
    error('The number of patent indicators being matched is not the same
       for the training and test datasets')
else
    % Determine the number of indicators used in the summary table:
    num_indicators = numel(test_data.Counts.summary_tables);
end
```

```
%% Construct test points matrix from the test technology dataset:
test_data.Points(:,1) = test_data.Counts.summary_tables(1).Final_Tables
    (:,1);
test_data.Transformed_Array(:,1) = test_data.Counts.summary_tables(1).
    Final_Tables(:,1);
test_data.Smoothed_Array(:,1) = test_data.Counts.summary_tables(1).
    Final_Tables(:,1);
test_data.Normalised_Array(:,1) = test_data.Counts.summary_tables(1).
    Final_Tables(:,1);
for i = 1:num_indicators
    test_data.Points(:,i+1) = test_data.Counts.summary_tables(i).
        Final_Tables(:,2);
    current_array = test_data.Points(:,i+1);

    % Transform the test data points by calculating the equivalent Inverse
    % Hyperbolic Sine values (this in itself is approximately equivalent to
    % calculating the natural logarithm of the values, except that this can
    % also handle data values equal to zero):
    test_data.Transformed_Array(:,i+1) = asinh(current_array);

    % Smooth the test data points by calculating three-year moving averages
    % for each of the patent indicators considered:
%     test_data.Smoothed_Array(:,i+1) = smooth(current_array,3);
    test_data.Smoothed_Array(:,i+1) = smooth(test_data.Transformed_Array(:,
        i+1),3);

    % Normalise the test data points by dividing all values by the maximum
    % recorded value for each of the patent indicators considered:
    test_data.Normalised_Array(:,i+1) = test_data.Smoothed_Array(:,i+1) /
        max(test_data.Smoothed_Array(:,i+1));
end

%% Determine the number of test points:
num_test_points = size(test_data.Normalised_Array,1);

%% Preallocate empty cell arrays for storing distance data:
distance_Aj_Bk = cell(1,numel(training_data));
distance_Aj0_Bk = cell(1,numel(training_data));
distance_Aj0_Bk_idx = cell(1,numel(training_data));

%% Determine the distance between all training points and test points:
for current_training_dataset = 1:numel(training_data)

    % Iterate through all test points (years):
    for k = 1:num_test_points
```

```
        % Select next test year set (i.e. Bk) to compare:
        current_test_set = test_data.Normalised_Array(k,2:end);

        % Iterate through all training points (years) for the current
        % training dataset:
        for j = 1:size(training_data(current_training_dataset).
            Normalised_Array,1)

            % Select next training year set (i.e. Aj) from the current
            % training dataset to compare:
            current_training_set = training_data(current_training_dataset).
                Normalised_Array(j,2:end);

            % Calculate the distance between the currently selected
            % training and test sets dist(Aj,Bk) by subtracting the test
            % set from the training set, squaring, summing all the elements
            % of the current distance vector together, and then
            % square-rooting:
            distance_Aj_Bk{1,current_training_dataset}(k,j) = (sum((
                current_training_set - current_test_set).^2))^0.5;
        end

        % Determine the minimum distance between the current test point and
        % all training points in the current training dataset in order to
        % identify the nearest training point in this dataset:
        [distance_Aj0_Bk{1,current_training_dataset}(k,1),
            distance_Aj0_Bk_idx{1,current_training_dataset}(k,1)] = min(
            distance_Aj_Bk{1,current_training_dataset}(k,:));

    end

end

%% Preallocate minimum distance, index, and label arrays:
all_distance_Aj0_Bk = [];
label_idx = zeros(num_test_points,1);
test_data.Label_set = zeros(num_test_points,2);

%% Combine the nearest training points from each training dataset into one
    array to determine overall minimum:
for current_training_dataset = 1:numel(training_data)
    if current_training_dataset == 1
        all_distance_Aj0_Bk = distance_Aj0_Bk{1,1};
    else
```

```
        all_distance_Aj0_Bk = [all_distance_Aj0_Bk,distance_Aj0_Bk{1,current_training_dataset}];
    end
end

%% Determine the nearest overall training point, and record the index:
[min_dist,min_dist_dataset] = min(all_distance_Aj0_Bk,[],2);

%% Use indices of nearest point from all training datasets to determine the corresponding TLC label to apply for the current test point:
for i = 1:num_test_points
    label_idx(i,1) = distance_Aj0_Bk_idx{1, min_dist_dataset(i)}(i);
    test_data.Label_set(i,1) = test_data.Normalised_Array(i,1);
    test_data.Label_set(i,2) = training_data(min_dist_dataset(i)).Label_set(label_idx(i,1),2);
end

% Save the matched TLC stages to a .MAT file in the current working
% directory:
savefile = ['Matched TLC stages - training dataset combination ',num2str(selected_training_datasets),'.mat'];
matched_TLC_stages = test_data.Label_set;
save(savefile,'matched_TLC_stages');

%% Determine screensize so that figures are scaled to the right size for the current monitor
% (scrsz == screen size vector [left, bottom, width, height])
scrsz = get(0,'ScreenSize');

% Extract patent indicator names from summary count tables:
table_names = cellstr(char(training_data(1).Counts.summary_tables(:).Names));

% %% Generate new figures showing the normalised development trends of all training patent indicators considered:
% for i = 1:numel(training_data)
%     figure_name = ['Development trends of patent indicators for ',lower(char(training_data(i).Technology)),' (TRAINING TECH - smoothed and normalised)'];
%     figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);
%     hold on
%
%     % Plot all training patent indicators on the same figure:
%     for j = 1:numel(table_names)
```

```
%         plot(training_data(i).Normalised_Array(:,1),training_data(i).Normalised_Array(:,j+1))
%     end
%
%     % Set figure title, x-axis, and y-axis labels:
%     title(figure_name,'FontSize',14);
%     xlabel('Year','FontSize',12);
%     ylabel('Normalised count','FontSize',12);
%
%     % Add legend to figure for development trends:
%     legend(strrep(table_names,'_',' '),'FontSize',12,'Location','northwest');
%
%     % Save the current figure to a .FIG file in the current working
%     % directory:
%     saveas(gcf,figure_name,'fig');
%     hold off
% end

%% Generate new figure showing the normalised development trends of the test patent indicators considered:
figure_name = ['Development trends of patent indicators for ',lower(deepestFolder),' (TEST TECH - smoothed and normalised)'];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);
hold on

% Plot all test patent indicators on the same figure:
for j = 1:numel(table_names)
    plot(test_data.Normalised_Array(:,1),test_data.Normalised_Array(:,j+1))
end

% Set figure title, x-axis, and y-axis labels:
title(figure_name,'FontSize',14);
xlabel('Year','FontSize',12);
ylabel('Normalised count','FontSize',12);

% Add legend to figure for development trends:
legend(strrep(table_names,'_',' '),'FontSize',12,'Location','northwest');

% Save the current figure to a .FIG file in the current working directory:
saveas(gcf,figure_name,'fig');
hold off

%% Generate new figure showing the progression of the matched TLC stages for the current test technology:
```

```matlab
figure_name = ['Matched TLC stages for ',lower(deepestFolder),' (TEST TECH) - training dataset combination ',num2str(selected_training_datasets)];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);
hold on

% Plot all test patent indicators on the same figure:
plot(test_data.Label_set(:,1),test_data.Label_set(:,2))

% Set figure title, x-axis, and y-axis labels:
title(figure_name,'FontSize',14);
xlabel('Year','FontSize',12);
ylabel('Matched TLC stage','FontSize',12);

% Add legend to figure for development trends:
false_handle_for_legend = zeros(5,1);
false_handle_for_legend(1) = plot(NaN,NaN,'-b');
false_handle_for_legend(2) = plot(NaN,NaN,'-b');
false_handle_for_legend(3) = plot(NaN,NaN,'-b');
false_handle_for_legend(4) = plot(NaN,NaN,'-b');
false_handle_for_legend(5) = plot(NaN,NaN,'-b');
legend(false_handle_for_legend,{'0 = Does not exist','1 = Emerging','2 = Growth','3 = Maturity','4 = Decline'},'FontSize',12,'Location','northwest');

% Save the current figure to a .FIG file in the current working directory:
saveas(gcf,figure_name,'fig');
hold off

toc()
```

Listing 4: statistical_analysis_segmented_clustering.m

```
% This script is used to conduct statistical analysis (consisting of
% K-Medoids clustering, Fisher's exact test, and leave-p-out
% cross-validation) on each of the patent indicators and patent indicator
% sets extracted for each technology using the 'extract_patent_metrics.m'
% script, which have subsequently been compiled in the 'Extracted patent
% indicators.xlsx' spreadsheet.

% This script is used to create spectrograms showing frequency content
% against time slots for each of the patent indicators extracted using the
% 'extract_patent_metrics.m' script, which have subsequently been compiled
% in the 'Extracted patent indicators.xlsx' spreadsheet.

clearvars
clear all
close all

tic()

% Request the user to choose the current working directory (NB: if no
% folder is selected in the user interface then the current working
% directory is taken to be the filepath) OR do not ask the user and just
% take the current directory:
% filepath = uigetdir;
patent_data_path = pwd;

% Identify the name of the selected working directory:
[upperPath,deepestFolder] = fileparts(patent_data_path);

% Set the number of clusters to group into:
num_clusters = 2;

% Set the number of technologies to leave-out in leave-p-out
% cross-validation:
num_technologies_to_remove = 1;

% Set the total number of patent indicators available in the excel file:
max_num_indicators = 10;

% Specify column index containing Technology Life Cycle stage data points
% (relative to order in technology_data.data structure):
TLC_stages_column_idx = 12;

% Preallocate empty cell and double arrays for storing indicator subsets:
indicator_subset = cell(1,max_num_indicators);

```

```
% Generate the indicator subsets to consider for clustering purposes:
% 1 = patents by application year
% 2 = patents by priority year
% 3 = corporates by priority year
% 4 = non-corporates by priority year
% 5 = set of inventors by priority year
% 6 = cited references by priority year
% 7 = cited patents by priority year
% 8 = distinct IPC subclass by priority year
% 9 = top 5 IPC subclass patents by priority year
% 10 = top 10 IPC subclass patents by priority year
for i = 1:max_num_indicators
    indicator_subset{i} = nchoosek(1:max_num_indicators,i);
    if i == 1
        indicator_subset_list = num2cell(indicator_subset{i},2);
    else
        indicator_subset_list = [indicator_subset_list; num2cell(
           indicator_subset{i},2)];
    end
end

% Calculate the total number of possible indicator subsets:
total_num_indicator_subsets = size(indicator_subset_list,1);

% Import compiled patent indicator data from the 'Extracted patent
% indicators.xlsx' spreadsheet:
technology_data = importdata('Extracted patent indicators.xlsx');

% Extract list of technologies included:
all_technologies = fieldnames(technology_data.data);

% Set the known cluster IDs for each of the technologies included in
% the patent indicator dataset, where 1 = technology arising as a result of
% previous stagnation and 2 = technology arising from presumption (NB:
% THESE VALUES ARE BASED ON PRIOR LITERATURE EVIDENCE AND NEED TO BE
% UDPATED/RESEQUENCED IF ANY NEW TECHNOLOGIES ARE ADDED TO/REMOVED FROM THE
% PATENT INDICATOR DATASET, OTHERWISE LATER PREDICTED VS. KNOWN CLUSTERING
% COMPARISONS WILL BE MISALIGNED OR WILL NOT HAVE THE CORRECT MATRIX
% DIMENSIONS):
technology_data.known_cluster_id.all_technologies =
   [1;1;2;1;2;2;1;2;1;2;1;1;2;1;1;1;2;2;2;1;1;1;2;2;2;1];

% Transform, smooth, and normalise the patent indicators considered:
for i = 1:numel(all_technologies)
    % Transform the patent indicator considered:
    for j = 1:max_num_indicators
```

```
        % Select the current indicator vector to transform, smooth, and
        % normalise:
        current_indicator_data = technology_data.data.(all_technologies{i})
            (1:end-1,1+j);

        % Transform the technology data points by calculating the
        % equivalent Inverse Hyperbolic Sine values (this in itself is
        % approximately equivalent to calculating the natural logarithm of
        % the values, except that this can also handle data values equal to
        % zero):
        technology_data.transformed_data.(all_technologies{i})(:,j) = asinh
            (current_indicator_data);

        % (UPDATE: The technology data points used in statistical
        % correlation analysis and significance testing should NOT be
        % smoothed, in line with the comments and illustration provided
        % here:
        % https://stats.stackexchange.com/questions/144013/smoothing-when-
            to-use-it-and-when-not-to
        % As such, the smoothing command below is no longer used and the
        % transformed data is used without any further smoothing. However,
        % smoothing the data for use in forecasting IS acceptable, and as
        % such the smoothing of time series conducted as part of the
        % subsequent functional data analysis process is not a problem)

        % ORIGINAL COMMANDS, NOW NO LONGER USED: Smooth the technology data
        % points by calculating three-year moving averages for each of the
        % patent indicators considered:
        technology_data.smoothed_data.(all_technologies{i})(:,j) = smooth(
            technology_data.transformed_data.(all_technologies{i})(:,j),3);
%           technology_data.smoothed_data.(all_technologies{i})(:,j) = smooth
    (current_indicator_data,3);
    end

    % Trim the array to remove the last few years were records have not yet
    % all been accounted for (i.e. it normally takes several years to
    % register all the patent records from a specific year, so the very end
    % years are likely to be incomplete). In these datasets, data after
    % 2011 seems to tail-off:
    trim_index = find(technology_data.data.(all_technologies{i})(:,1) >
        2011);
    technology_data.trimmed_data.(all_technologies{i}) = technology_data.
        transformed_data.(all_technologies{i});
    technology_data.trimmed_data.(all_technologies{i})(trim_index,:) = [];

    % Normalise the patent indicator considered:
```

```
    for j = 1:max_num_indicators
        % Normalise the technology data points by dividing all values by
        % the maximum recorded value for each of the patent indicators
        % considered:
        technology_data.normalised_data.(all_technologies{i})(:,j) =
            technology_data.trimmed_data.(all_technologies{i})(:,j) / max(
            technology_data.trimmed_data.(all_technologies{i})(:,j));
%         technology_data.normalised_data.(all_technologies{i})(:,j) =
    technology_data.smoothed_data.(all_technologies{i})(:,j) / max(
    technology_data.smoothed_data.(all_technologies{i})(:,j));
    end

    % Add normalised time and Technology Life Cycle columns back on to
    % normalised datasets:
    technology_data.normalised_data.(all_technologies{i}) = [
        technology_data.normalised_data.(all_technologies{i}),(0:1/(size(
        technology_data.normalised_data.(all_technologies{i}),1) - 1):1)'];
    technology_data.normalised_data.(all_technologies{i}) = [
        technology_data.normalised_data.(all_technologies{i}),
        technology_data.data.(all_technologies{i})(1:end-(1 + size(
        trim_index,1)),12:19)];
end

% Determine the most advanced technology life cycle stage reached by each
% technology:
max_TLC_stage = zeros(numel(all_technologies),1);
for i = 1:numel(all_technologies)
    max_TLC_stage(i) = max(technology_data.normalised_data.(
        all_technologies{i})(:,TLC_stages_column_idx));
end

% Determine the minimum technology life cycle stage covered by each
% technology dataset:
min_TLC_stage = zeros(numel(all_technologies),1);
for i = 1:numel(all_technologies)
    min_TLC_stage(i) = min(technology_data.normalised_data.(
        all_technologies{i})(:,TLC_stages_column_idx));
end

% Filter out data from technologies with insufficient data records:
technology_data_filtered = technology_data;
technology_data_filtered.known_cluster_id.filtered = technology_data.
    known_cluster_id.all_technologies;
% fields_to_remove = {};
technologies_with_insufficient_records = {all_technologies{1},
    all_technologies{5},all_technologies{20}};
```

```
technology_data_filtered.data = rmfield(technology_data_filtered.data,
    technologies_with_insufficient_records);
technology_data_filtered.textdata = rmfield(technology_data_filtered.
    textdata,technologies_with_insufficient_records);
technology_data_filtered.colheaders = rmfield(technology_data_filtered.
    colheaders,technologies_with_insufficient_records);
technology_data_filtered.transformed_data = rmfield(
    technology_data_filtered.transformed_data,
    technologies_with_insufficient_records);
technology_data_filtered.smoothed_data = rmfield(technology_data_filtered.
    smoothed_data,technologies_with_insufficient_records);
technology_data_filtered.trimmed_data = rmfield(technology_data_filtered.
    trimmed_data,technologies_with_insufficient_records);
technology_data_filtered.normalised_data = rmfield(technology_data_filtered
    .normalised_data,technologies_with_insufficient_records);
technology_data_filtered.all_TLC_stages = technology_data_filtered.
    normalised_data;
elements_to_remove = ismember(all_technologies,
    technologies_with_insufficient_records);
technology_data_filtered.known_cluster_id.filtered(elements_to_remove) =
    [];
technology_data_filtered.known_cluster_id.all_TLC_stages =
    technology_data_filtered.known_cluster_id.filtered;

% Filter datasets corresponding to technologies that are registered to
% have passed/be passing through the emergence stage of the Technology Life
% Cycle:
technologies_to_exclude_emergence = [all_technologies(max_TLC_stage < 1);
    all_technologies(min_TLC_stage > 1)];
technology_data_filtered.emergence = rmfield(technology_data.
    normalised_data,union(technologies_with_insufficient_records,
    technologies_to_exclude_emergence));
elements_to_remove_emergence = ismember(all_technologies,union(
    technologies_with_insufficient_records,technologies_to_exclude_emergence
    ));
technology_data_filtered.known_cluster_id.emergence = technology_data.
    known_cluster_id.all_technologies;
technology_data_filtered.known_cluster_id.emergence(
    elements_to_remove_emergence) = [];

% Filter datasets corresponding to technologies that are registered to
% have passed/be passing through the growth stage of the Technology Life
% Cycle:
technologies_to_exclude_growth = [all_technologies(max_TLC_stage < 2);
    all_technologies(min_TLC_stage > 2)];
```

```
technology_data_filtered.growth = rmfield(technology_data.normalised_data,
    union(technologies_with_insufficient_records,
    technologies_to_exclude_growth));
elements_to_remove_growth = ismember(all_technologies,union(
    technologies_with_insufficient_records,technologies_to_exclude_growth));
technology_data_filtered.known_cluster_id.growth = technology_data.
    known_cluster_id.all_technologies;
technology_data_filtered.known_cluster_id.growth(elements_to_remove_growth)
     = [];

% Filter datasets corresponding to technologies that are registered to
% have passed/be passing through the maturity stage of the Technology Life
% Cycle:
technologies_to_exclude_maturity = [all_technologies(max_TLC_stage < 3);
    all_technologies(min_TLC_stage > 3)];
technology_data_filtered.maturity = rmfield(technology_data.normalised_data
    ,union(technologies_with_insufficient_records,
    technologies_to_exclude_maturity));
elements_to_remove_maturity = ismember(all_technologies,union(
    technologies_with_insufficient_records,technologies_to_exclude_maturity)
    );
technology_data_filtered.known_cluster_id.maturity = technology_data.
    known_cluster_id.all_technologies;
technology_data_filtered.known_cluster_id.maturity(
    elements_to_remove_maturity) = [];

% Filter datasets corresponding to technologies that are registered to
% have passed/be passing through the decline stage of the Technology Life
% Cycle:
technologies_to_exclude_decline = [all_technologies(max_TLC_stage < 4);
    all_technologies(min_TLC_stage > 4)];
technology_data_filtered.decline = rmfield(technology_data.normalised_data,
    union(technologies_with_insufficient_records,
    technologies_to_exclude_decline));
elements_to_remove_decline = ismember(all_technologies,union(
    technologies_with_insufficient_records,technologies_to_exclude_decline))
    ;
technology_data_filtered.known_cluster_id.decline = technology_data.
    known_cluster_id.all_technologies;
technology_data_filtered.known_cluster_id.decline(
    elements_to_remove_decline) = [];

% Extract list of technologies included:
technology.all_TLC_stages = fieldnames(technology_data_filtered.data);
technology.emergence = fieldnames(technology_data_filtered.emergence);
technology.growth = fieldnames(technology_data_filtered.growth);
```

```
technology.maturity = fieldnames(technology_data_filtered.maturity);
technology.decline = fieldnames(technology_data_filtered.decline);

% Compile list of technology life cycle stages considered:
TLC_stages = fieldnames(technology);

% Limit data points within these datasets to only those points classed as
% being during the 'emergence' technology life cycle stage:
for i = 1:numel(technology.emergence)
    technology_data_filtered.emergence.(technology.emergence{i}) =
        technology_data_filtered.emergence.(technology.emergence{i})((
        technology_data_filtered.emergence.(technology.emergence{i})(:,
        TLC_stages_column_idx) == 1),:);
end

% Limit data points within these datasets to only those points classed as
% being during the 'growth' technology life cycle stage:
for i = 1:numel(technology.growth)
    technology_data_filtered.growth.(technology.growth{i}) =
        technology_data_filtered.growth.(technology.growth{i})((
        technology_data_filtered.growth.(technology.growth{i})(:,
        TLC_stages_column_idx) == 2),:);
end

% Limit data points within these datasets to only those points classed as
% being during the 'maturity' technology life cycle stage:
for i = 1:numel(technology.maturity)
    technology_data_filtered.maturity.(technology.maturity{i}) =
        technology_data_filtered.maturity.(technology.maturity{i})((
        technology_data_filtered.maturity.(technology.maturity{i})(:,
        TLC_stages_column_idx) == 3),:);
end

% Limit data points within these datasets to only those points classed as
% being during the 'decline' technology life cycle stage:
for i = 1:numel(technology.decline)
    technology_data_filtered.decline.(technology.decline{i}) =
        technology_data_filtered.decline.(technology.decline{i})((
        technology_data_filtered.decline.(technology.decline{i})(:,
        TLC_stages_column_idx) == 4),:);
end

% Store patent indicator column names:
patent_indicator_column_names = {'patents by application year';'patents by
    priority year';...
    'corporates by priority year';'non corporates by priority year';...
```

```
    'set of inventors by priority year';'cited references by priority year'
       ;...
    'cited patents by priority year';'distinct IPC subclass by priority
       year';...
    'top 5 IPC subclass patents by priority year';'top 10 IPC subclass
       patents by priority year'};

% Set figures generated to be invisible by default:
set(0,'DefaultFigureVisible','off')

% Determine screensize so that figures are scaled to the right size for the
% current monitor (scrsz == screen size vector [left, bottom, width,
% height])
scrsz = get(0,'ScreenSize');

%% Move to the relevant 'Statistics results' folder
% (UF = unfiltered, F = filtered, IHS = Inverted Hyperbolic Sine function
% applied, S = smoothed and normalised, sub = using subsets of patent
% indicators, LOOCV = 'leave-one-out' cross-validation, LHOCV =
% 'leave-half-the-technologies-out' cross-validation):

% cd('Statistics (Final - L1OCV)')
cd('Statistics (Final - L1OCV -FOSC)')
% cd('Statistics (Final - L2OCV)')
% cd('Statistics (Final - L3OCV)')
% cd('Statistics (Final - L4OCV)')
% cd('Statistics (Final - L5OCV)')
% cd('Statistics (Final - L6OCV)')
% cd('Statistics (Test)')

%% Preallocate empty double and cell arrays for storing distance data:
for stage = 1:numel(TLC_stages)
    DTW_distance_subset_indicator.(TLC_stages{stage}) = zeros(numel(
       technology.(TLC_stages{stage})),numel(technology.(TLC_stages{stage})
       ),total_num_indicator_subsets);
    current_technology_warping_path.(TLC_stages{stage}) = cell(numel(
       technology.(TLC_stages{stage})),numel(technology.(TLC_stages{stage})
       ),total_num_indicator_subsets);
    comparison_technology_warping_path.(TLC_stages{stage}) = cell(numel(
       technology.(TLC_stages{stage})),numel(technology.(TLC_stages{stage})
       ),total_num_indicator_subsets);
end

%% Determine relative distances between each respective pair of technology
   patent indicator curves generated when comparing each technology to
```

```
every other technology for each of the patent indicator subsets considered, for each Technology Life Cycle stage:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % This is done using the Dynamic Time Warping (DTW) approach for each
    % of the technologies included in the patent indicators dataset:
    for i = 1:numel(technology.(TLC_stages{stage}))
        % Select the current indicator set for analysis:
        current_technology_data = technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){i});

        % Iterate through the comparison technology indicator sets:
        for j = 1:numel(technology.(TLC_stages{stage}))
            % Select the technology indicator set to measure distance
            % against:
            comparison_technology_data = technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j});

            % Iterate through each indicator subset to base clustering on:
            for k = 1:total_num_indicator_subsets
                % Select the current patent indicator subset to measure
                % distances against:
                current_indicator_subset = indicator_subset_list{k,1};

                % Generate a new figure for comparing original and aligned
                % signals:
%                 figure_name = ['DTW of ',technology.(TLC_stages{stage}){j},' relative to ',technology.(TLC_stages{stage}){i},' - ',(TLC_stages{stage}),' (INDICATOR SUBSET ',num2str(k),')'];
%                 figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);

                % Calculate the distance between technologies using only
                % the selected subset of patent indicators:
                [DTW_distance_subset_indicator.(TLC_stages{stage})(i,j,k),current_technology_warping_path.(TLC_stages{stage}){i,j,k}(1,:),comparison_technology_warping_path.(TLC_stages{stage}){i,j,k}(1,:)] = dtw(current_technology_data(:,current_indicator_subset)',comparison_technology_data(:,current_indicator_subset)');
%                 dtw(current_technology_data(:,current_indicator_subset)',comparison_technology_data(:,current_indicator_subset)');

                % Set subplots to be invisible now, but visible when opened
                % later:
```

```
%                    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible
    '',''on'')')
%                    saveas(gcf,figure_name,'fig')
                end

            end

        %       toc()

        end

        % toc()

end

% toc()

%% Save all variables to a MAT file:
save('statistical_analysis.mat')

toc()

%% Set figures generated to be visible again by default:
% set(0,'DefaultFigureVisible','on')

%% Cluster the technology time series either based on individual patent
    indicator distances, or by considering distances measured when
    considering all (or a subset) of patent indicators simultaneously.

%% Determine technology clusters based on considering a specified subset of
     patent indicators simultaneously:

% Preallocate empty double and cell arrays for storing cluster ID results
% for each subset:
for stage = 1:numel(TLC_stages)
    cluster_ID_subset.(TLC_stages{stage}) = zeros(numel(technology.(
        TLC_stages{stage})),total_num_indicator_subsets);
    medoid_locations_idx_subset.(TLC_stages{stage}) = zeros(num_clusters,
        total_num_indicator_subsets);
    cluster_percentage_difference.(TLC_stages{stage}) = zeros(1,
        total_num_indicator_subsets);
    realigned_cluster_ID_subsets.(TLC_stages{stage}) = zeros(numel(
        technology.(TLC_stages{stage})),total_num_indicator_subsets);
    significance.(TLC_stages{stage}) = zeros(1,total_num_indicator_subsets)
        ;
    p_value.(TLC_stages{stage}) = zeros(1,total_num_indicator_subsets);
```

```
    group_maps.(TLC_stages{stage}) = cell(1,total_num_indicator_subsets);
    confusion_matrix.(TLC_stages{stage}) = cell(1,
        total_num_indicator_subsets);
    p_value_stats.(TLC_stages{stage}) = cell(1,total_num_indicator_subsets)
        ;
end

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    for k = 1:total_num_indicator_subsets
        % Determine K-Medoid clusters for the current subset of patent
        % indicators:
        [cluster_ID_subset.(TLC_stages{stage})(:,k),medoid_locations_subset
            ,within_cluster_sum_subset,distance_to_medoid_subset,
            medoid_locations_idx_subset.(TLC_stages{stage})(:,k),info_subset
            ] = kmedoids(DTW_distance_subset_indicator.(TLC_stages{stage})
            (:,:,k),num_clusters,'Algorithm','pam');

        % Realign group mappings in the predicted cluster ID results to
        % match those of the known cluster groups:
        group_mappings_A = cluster_ID_subset.(TLC_stages{stage})(:,k);
        group_mappings_B = technology_data_filtered.known_cluster_id.(
            TLC_stages{stage});
        [group_map, realigned_predicted_cluster_IDs] = group_mappings(
            group_mappings_A,group_mappings_B);
        group_maps.(TLC_stages{stage}){k} = group_map;
        realigned_cluster_ID_subsets.(TLC_stages{stage})(:,k) =
            realigned_predicted_cluster_IDs';

        % Calculate the confusion matrix for the current specified subset
        % of indicators:
        confusion_matrix.(TLC_stages{stage}){k} = confusionmat(
            technology_data_filtered.known_cluster_id.(TLC_stages{stage}),
            realigned_predicted_cluster_IDs);

        % Use Fisher's exact test to determine the statistical significance
        % (i.e. the two-tail p-value) of the current specified subset of
        % indicators. This tests the null hypothesis that the current
        % observed group labels are not related to the predicted (i.e.
        % literature-based) group labels. As such a p-value of less than
        % 0.05 implies that the null hypothesis is rejected, and that there
        % is a statistical significance between the current specified
        % patent indicator subset and the expected groupings:
        if num_clusters == 2
```

```
            [significance.(TLC_stages{stage})(k),p_value.(TLC_stages{stage})(k),p_value_stats.(TLC_stages{stage}){k}] = fishertest(confusion_matrix.(TLC_stages{stage}){k});
        elseif num_clusters == 3
            p_value.(TLC_stages{stage})(k) = myfisher33(confusion_matrix.(TLC_stages{stage}){k});
            if p_value.(TLC_stages{stage})(k) <= 0.05
                significance.(TLC_stages{stage})(k) = 1;
            else
                significance.(TLC_stages{stage})(k) = 0;
            end
        end

        % Create target and output matrices for use in confusion plot for
        % the current specified subset of indicators:
        for j = 1:num_clusters
            if j == 1
                targets = (technology_data_filtered.known_cluster_id.(TLC_stages{stage}) == 1)';
                outputs = realigned_predicted_cluster_IDs == 1;
            else
                targets = [targets; (technology_data_filtered.known_cluster_id.(TLC_stages{stage}) == j)'];
                outputs = [outputs; realigned_predicted_cluster_IDs == j];
            end
        end

        % Convert target and output matrices to double arrays:
        targets = double(targets);
        outputs = double(outputs);

        % Plot the classification confusion matrix for the current
        % specified subset of indicators:
%         figure_name = ['Classification confusion matrix based on patent indicators subset ',num2str(k),' - ',TLC_stages{stage}];
%         figure('Name',figure_name,'NumberTitle','off','OuterPosition',[1, 1, scrsz(3), scrsz(4)]);
%         hold on;
%         plotconfusion(targets,outputs);
%
%         % Add title to figure:
%         title(figure_name);
%
%         % Set subplots to be invisible now, but visible when opened later:
```

```
%         set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
%
%         % Save figure:
%         saveas(gcf,figure_name,'fig');
%         hold off;

        % Compare the predicted cluster IDs to the known cluster IDs
        % (taken from literature evidence) using hamming distance between
        % vectors:
        cluster_percentage_difference.(TLC_stages{stage})(k) = pdist2(technology_data_filtered.known_cluster_id.(TLC_stages{stage})',realigned_predicted_cluster_IDs,'hamming');

        % Plot the time series clusters based on considering a specified
        % subset of patent indicators simultaneously:
%         figure_name = ['K-medoids clustering of technologies based on patent indicators subset ',num2str(k),' - ',TLC_stages{stage},' (',patent_indicator_column_names{1},')'];
%         figure('Name',figure_name,'NumberTitle','off','OuterPosition',[1, 1, scrsz(3), scrsz(4)]);
%         hold on;
%
%         for j = 1:numel(technology.(TLC_stages{stage}))
%             if realigned_predicted_cluster_IDs(j) == 1
%                 plot(technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,11),technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,1),'r-');
%             elseif realigned_predicted_cluster_IDs(j) == 2
%                 plot(technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,11),technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,1),'b-');
%             elseif realigned_predicted_cluster_IDs(j) == 3
%                 plot(technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,11),technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){j})(:,1),'g-');
%             end
%         end
%
%         % Plot the medoid time series when considering a specified subset
%         % of patent indicators simultaneously:
%         for j = 1:num_clusters
%             plot(technology_data_filtered.(TLC_stages{stage}).(technology.(TLC_stages{stage}){medoid_locations_idx_subset.(TLC_stages{stage})(j,k)})(:,11),technology_data_filtered.(TLC_stages{stage}).(technology.(
```

```
    TLC_stages{stage}){medoid_locations_idx_subset.(TLC_stages{stage})(j,k)
    })(:,1),'co','MarkerSize',7,'LineWidth',1.5);
%           end
%
%           % Add legend to the technology time series clusters:
%           legend(strrep(technology.(TLC_stages{stage}),'_',' '),'FontSize
    ',12,'Location','northwest');
%
%           % Add title to figure:
%           title(figure_name);
%
%           % Set subplots to be invisible now, but visible when opened later
    :
%           set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')
    ')
%
%           % Save figure:
%           saveas(gcf,figure_name,'fig');
%           hold off;
    end

%     toc()
end

toc()

%% Set figures generated to be visible again by default:
set(0,'DefaultFigureVisible','on')

%% Plot histograms based on the minimum difference to the known cluster IDs
    , as well as those indicator subsets that are statistically significant:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % Locate indicator subsets giving the minimum difference to the known
    % cluster IDs, as well as those indicator subsets that are
    % statistically significant:
    [min_cluster_difference_value,min_cluster_difference_index] = min(
        cluster_percentage_difference.(TLC_stages{stage}));
    min_difference_subsets.(TLC_stages{stage}) = indicator_subset_list(find
        (cluster_percentage_difference.(TLC_stages{stage}) ==
        min_cluster_difference_value));
    significance_logical = logical(significance.(TLC_stages{stage}));
    statistically_significant_subsets.(TLC_stages{stage}) =
        indicator_subset_list(significance_logical);
```

```
% Compare lists of minimum difference and statistically significant
% subsets:
common_subsets_stat_significance.(TLC_stages{stage}) = ismember(cellfun
    (@num2str,statistically_significant_subsets.(TLC_stages{stage}),'
    UniformOutput',0),cellfun(@num2str,min_difference_subsets.(
    TLC_stages{stage}),'UniformOutput',0));
common_subsets_min_difference.(TLC_stages{stage}) = ismember(cellfun(
    @num2str,min_difference_subsets.(TLC_stages{stage}),'UniformOutput'
    ,0),cellfun(@num2str,statistically_significant_subsets.(TLC_stages{
    stage}),'UniformOutput',0));

% Plot a histogram of the most frequently occuring indicators in
% identified best patent indicator subsets:
figure_name = ['Histogram of most frequently occuring patent indicators
     in minimum hamming difference cluster predictions - ',TLC_stages{
    stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on;
histogram([min_difference_subsets.(TLC_stages{stage}){1:end}]);

% Add title, X, and Y labels to figure:
title(figure_name);
xlabel('Patent indicator','FontSize',12)
ylabel('Count','FontSize',12)

% Save figure:
saveas(gcf,figure_name,'fig');
hold off;

% Plot a histogram of the most frequently occuring indicators in
% identified statistically significant patent indicator subsets:
figure_name = ['Histogram of most frequently occuring patent indicators
     in statistically significant cluster predictions - ',TLC_stages{
    stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on;
histogram([statistically_significant_subsets.(TLC_stages{stage}){1:end
    }]);

% Add title, X, and Y labels to figure:
title(figure_name);
xlabel('Patent indicator','FontSize',12)
ylabel('Count','FontSize',12)
```

```
    % Save figure:
    saveas(gcf,figure_name,'fig');
    hold off;
end

%% Save all variables to a MAT file:
save('statistical_analysis.mat');

toc()

%% Run 'leave-p-out' cross-validation:
% The sections of the script that follow look at conducting leave-p-out
% cross-validation of each of the patent indicator subsets that have been
% identified as providing a statistically significant correlation to the
% expected technology groupings. The analysis in the sections below works
% on leave-half-the-technologies-out cross-validation (to give the largest
% sample for cross-validation). Alternatively, leave-one-out
% cross-validation can be used or any other leave-p-out variant by
% specifiying an alternative number of technologies to omit from the
% training subset permutations (see line where
% 'training_technology_subsets' are defined). This follows on from
% discussions with the Bristol University Statistics Clinic on the
% 22_03_17. For further details see
% https://en.wikipedia.org/wiki/Cross-validation_(statistics)

%% Determine relative distances between each respective pair of technology
    patent indicator curves generated when comparing each technology to
    every other technology for each of the statistically significant patent
    indicator subsets for the current technology training dataset:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % Create training technology subsets based on
    % leave-half-the-technologies-out cross-validation:
%     training_technology_subsets.(TLC_stages{stage}) = nchoosek(1:numel(
    technology.(TLC_stages{stage})),numel(technology.(TLC_stages{stage})) -
    floor(numel(technology.(TLC_stages{stage}))/2));

    % Alternatively, create training technology subsets based on
    % leave-p-out cross-validation:
    training_technology_subsets.(TLC_stages{stage}) = nchoosek(1:numel(
        technology.(TLC_stages{stage})),numel(technology.(TLC_stages{stage})
        ) - num_technologies_to_remove);

    % Determine test technology subsets based on the corresponding training
    % technology subsets:
```

```
test_technology_subsets.(TLC_stages{stage}) = zeros(size(
    training_technology_subsets.(TLC_stages{stage}),1),numel(technology
    .(TLC_stages{stage})) - size(training_technology_subsets.(TLC_stages
    {stage}),2));
for i = 1:size(training_technology_subsets.(TLC_stages{stage}),1)
     test_technology_subsets.(TLC_stages{stage})(i,:) = setdiff(1:numel(
         technology.(TLC_stages{stage})),training_technology_subsets.(
         TLC_stages{stage})(i,:));
end

% Extract the total number of statistically significant patent
% indicator subset combinations:
total_num_statistically_significant_indicator_subsets.(TLC_stages{stage
    }) = numel(statistically_significant_subsets.(TLC_stages{stage}));

% Create matrices corresponding to training and test technology subset
% indices respectively:
training_technology_subsets_idx.(TLC_stages{stage}) = zeros(size(
    training_technology_subsets.(TLC_stages{stage}),2),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(training_technology_subsets.(TLC_stages{stage}),1));
test_technology_subsets_idx.(TLC_stages{stage}) = zeros(size(
    test_technology_subsets.(TLC_stages{stage}),2),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
for i = 1:size(training_technology_subsets.(TLC_stages{stage}),1)
     training_technology_subsets_idx.(TLC_stages{stage})(:,:,i) = repmat
         (training_technology_subsets.(TLC_stages{stage})(i,:)',1,
         total_num_statistically_significant_indicator_subsets.(
         TLC_stages{stage}));
     test_technology_subsets_idx.(TLC_stages{stage})(:,:,i) = repmat(
         test_technology_subsets.(TLC_stages{stage})(i,:)',1,
         total_num_statistically_significant_indicator_subsets.(
         TLC_stages{stage}));
end

% Preallocate empty double arrays for storing distance data:
DTW_distance_training_technology_subset_indicator.(TLC_stages{stage}) =
     zeros(floor(numel(technology.(TLC_stages{stage}))/2),floor(numel(
    technology.(TLC_stages{stage}))/2),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(training_technology_subsets.(TLC_stages{stage}),1));

% Determine relative distances between each respective pair of
% technology patent indicator curves generated when comparing each
% technology to every other technology for each of the statistically
```

```
    % significant patent indicator subsets for the current technology
    % training dataset. This is done using the Dynamic Time Warping (DTW)
    % approach for each of the technologies included in the patent
    % indicators dataset:
    for training_technology_subset = 1:size(training_technology_subsets.(
        TLC_stages{stage}),1)
        % Select the current training technology subset for analysis:
        current_training_technology_subset = training_technology_subsets.(
            TLC_stages{stage})(training_technology_subset,:);

        % Iterate through the current training technology indicator sets:
        for i = 1:numel(current_training_technology_subset)
            % Select the current indicator set for analysis:
            current_technology_data = technology_data_filtered.(TLC_stages{
                stage}).(technology.(TLC_stages{stage}){
                current_training_technology_subset(i)});

            % Iterate through the comparison technology indicator sets:
            for j = 1:numel(current_training_technology_subset)
                % Select the technology indicator set to measure distance
                % against:
                comparison_technology_data = technology_data_filtered.(
                    TLC_stages{stage}).(technology.(TLC_stages{stage}){
                    current_training_technology_subset(j)});

                % Iterate through each statistically significantly
                % indicator subset to base clustering on:
                for k = 1:
                    total_num_statistically_significant_indicator_subsets.(
                    TLC_stages{stage})
                    % Select the current statistically significant
                    % indicator subset to measure distances against:
                    current_indicator_subset =
                        statistically_significant_subsets.(TLC_stages{stage
                        }){k,1};

                    % Calculate the distance between training technologies
                    % using only the selected statistically significant
                    % subset of indicators (as symetric matrix, only need
                    % to calculate the upper diagonal):
                    if i <= j
                        DTW_distance_training_technology_subset_indicator.(
                            TLC_stages{stage})(i,j,k,
                            training_technology_subset) = dtw(
                            current_technology_data(:,
                            current_indicator_subset)',
```

```
                            comparison_technology_data(:,
                            current_indicator_subset)');
                    else
                        DTW_distance_training_technology_subset_indicator.(
                            TLC_stages{stage})(i,j,k,
                            training_technology_subset) =
                            DTW_distance_training_technology_subset_indicator
                            .(TLC_stages{stage})(j,i,k,
                            training_technology_subset);
                    end

                end

            end

        end

    %     toc()

    end

%     toc()

end

toc()

%% Save all variables to a MAT file:
save('statistical_analysis.mat');

%% Determine technology clusters based on the current training technology
    subset, whilst only considering statistically significant subsets of
    patent indicators simultaneously:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % Preallocate empty double and cell arrays for storing cluster ID
    % results and distance data for each cross-validation subset:
    cluster_ID_training_technologies.(TLC_stages{stage}) = zeros(size(
        training_technology_subsets.(TLC_stages{stage}),2),
        total_num_statistically_significant_indicator_subsets.(TLC_stages{
        stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
    medoid_locations_idx_cross_validation.(TLC_stages{stage}) = zeros(
        num_clusters,total_num_statistically_significant_indicator_subsets.(
        TLC_stages{stage}),size(test_technology_subsets.(TLC_stages{stage})
        ,1));
```

```
DTW_distance_test_technology_subset_indicator.(TLC_stages{stage}) =
    zeros(num_clusters,size(test_technology_subsets.(TLC_stages{stage})
    ,2),total_num_statistically_significant_indicator_subsets.(
    TLC_stages{stage}),size(test_technology_subsets.(TLC_stages{stage})
    ,1));
cluster_ID_test_technologies.(TLC_stages{stage}) = zeros(size(
    test_technology_subsets.(TLC_stages{stage}),2),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
cluster_ID_cross_validation.(TLC_stages{stage}) = zeros(numel(
    technology.(TLC_stages{stage})),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
realigned_cluster_ID_cross_validation.(TLC_stages{stage}) = zeros(numel
    (technology.(TLC_stages{stage})),
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
num_misclassified_test_technologies.(TLC_stages{stage}) = zeros(
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));
group_maps_cross_validation.(TLC_stages{stage}) = cell(
    total_num_statistically_significant_indicator_subsets.(TLC_stages{
    stage}),size(test_technology_subsets.(TLC_stages{stage}),1));

% Iterate through technology test subsets:
for test_technology_subset = 1:size(test_technology_subsets.(TLC_stages
    {stage}),1)
     % Select the current test technology subset for analysis:
     current_test_technology_subset = test_technology_subsets.(
         TLC_stages{stage})(test_technology_subset,:);

     % Iterate through subsets of statistically significant patent
     % indicators:
     for k = 1:total_num_statistically_significant_indicator_subsets.(
         TLC_stages{stage})
          % Determine K-Medoid clusters for the current statistically
          % significant patent indicators subset based on current
          % training technology subset:
          [cluster_ID_training_technologies.(TLC_stages{stage})(:,k,
              test_technology_subset),medoid_locations_cross_validation,
              within_cluster_sum_cross_validation,
              distance_to_medoid_cross_validation,
              medoid_locations_idx_cross_validation.(TLC_stages{stage})(:,
              k,test_technology_subset),info_cross_validation] = kmedoids(
              DTW_distance_training_technology_subset_indicator.(
```

```
        TLC_stages{stage})(:,:,k,test_technology_subset),
        num_clusters,'Algorithm','pam');

    % Select the current statistically significant indicator subset
    % to measure distances against:
    current_indicator_subset = statistically_significant_subsets.(
        TLC_stages{stage}){k,1};

    % Iterate through the current test technology indicator sets:
    for i = 1:numel(current_test_technology_subset)
        % Select the current indicator set for analysis:
        current_technology_data = technology_data_filtered.(
            TLC_stages{stage}).(technology.(TLC_stages{stage}){
            current_test_technology_subset(i)});

        % Iterate through the comparison medoid technologies:
        for j = 1:num_clusters
            % Select the technology indicator set to measure
            % distance against:
            comparison_medoid_technology_data =
                technology_data_filtered.(TLC_stages{stage}).(
                technology.(TLC_stages{stage}){
                medoid_locations_idx_cross_validation.(TLC_stages{
                stage})(j,k,test_technology_subset)});

            % Use Dynamic Time Warping to determine the distance
            % between each technology in the current test
            % technology subset and the medoids located using the
            % training technology subsets:
            DTW_distance_test_technology_subset_indicator.(
                TLC_stages{stage})(j,i,k,test_technology_subset) =
                dtw(current_technology_data(:,
                current_indicator_subset)',
                comparison_medoid_technology_data(:,
                current_indicator_subset)');
        end

        % Use the minimum distance to determine the cluster label
        % to apply to the current test technology (aligned to group
        % labels assigned based on training technology subsets -
        % NB: the current group labels will subsequently need to be
        % realigned to match the known cluster IDs, but this is
        % done after all the test technologies have been mapped to
        % the existing groupings to avoid any unnecessary group
        % label translation errors at this stage):
```

```
        [~,nearest_medoid_idx] = min(
            DTW_distance_test_technology_subset_indicator.(
            TLC_stages{stage})(:,i,k,test_technology_subset));
        cluster_ID_test_technologies.(TLC_stages{stage})(i,k,
            test_technology_subset) =
            cluster_ID_training_technologies.(TLC_stages{stage})(
            medoid_locations_idx_cross_validation.(TLC_stages{stage
            })(nearest_medoid_idx,k,test_technology_subset),k,
            test_technology_subset);

    end

    % Recombine training and test technology cluster IDs in their
    % correct order:
    cluster_ID_cross_validation.(TLC_stages{stage})(
        training_technology_subsets_idx.(TLC_stages{stage})(:,k,
        test_technology_subset),k,test_technology_subset) =
        cluster_ID_training_technologies.(TLC_stages{stage})(:,k,
        test_technology_subset);
    cluster_ID_cross_validation.(TLC_stages{stage})(
        test_technology_subsets_idx.(TLC_stages{stage})(:,k,
        test_technology_subset),k,test_technology_subset) =
        cluster_ID_test_technologies.(TLC_stages{stage})(:,k,
        test_technology_subset);

    % Realign group mappings in the predicted cluster ID results to
    % match those of the known cluster groups:
    [group_map, realigned_predicted_cluster_IDs] = group_mappings(
        cluster_ID_cross_validation.(TLC_stages{stage})(:,k,
        test_technology_subset),technology_data_filtered.
        known_cluster_id.(TLC_stages{stage}));
    group_maps_cross_validation.(TLC_stages{stage}){k,
        test_technology_subset} = group_map;
    realigned_cluster_ID_cross_validation.(TLC_stages{stage})(:,k,
        test_technology_subset) = realigned_predicted_cluster_IDs';

    % Calculate the number of test technologies that have been
    % misclustered based on the current training technology subset,
    % using the current statistically significant subset of patent
    % indicators:
    predicted_test_cluster_IDs =
        realigned_cluster_ID_cross_validation.(TLC_stages{stage})(
        test_technology_subsets_idx.(TLC_stages{stage})(:,k,
        test_technology_subset),k,test_technology_subset);
    corresponding_known_cluster_IDs = technology_data_filtered.
        known_cluster_id.(TLC_stages{stage})(
```

```
                test_technology_subsets_idx.(TLC_stages{stage})(:,k,
                test_technology_subset));
            misclassified_test_technologies = predicted_test_cluster_IDs ~=
                 corresponding_known_cluster_IDs;
            num_misclassified_test_technologies.(TLC_stages{stage})(k,
                test_technology_subset) = sum(
                misclassified_test_technologies);

        end

    %     toc()

    end

%     toc()

end

toc()

%% Rank the statistically significant patent indicator subsets based on
    their respective ability to predict the correct technology groupings
    using different training technologies:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % Calculate the average number of test technologies misclassified for
    % each statistically significant patent indicator subset for different
    % training technology subsets:
    statistically_significant_subsets_avg_misclassified.(TLC_stages{stage})
         = sum(num_misclassified_test_technologies.(TLC_stages{stage}),2) /
        size(num_misclassified_test_technologies.(TLC_stages{stage}),2);

    % Rank each statistically significant patent indicator subset based on
    % the average number of test technologies misclassified for different
    % training technology subsets:
    [statistically_significant_subsets_sorted.(TLC_stages{stage}),
        statistically_significant_subsets_rank.(TLC_stages{stage})] = sort(
        statistically_significant_subsets_avg_misclassified.(TLC_stages{
        stage}));

    % Locate the statistically significant patent indicator subsets giving
    % the minimum average number of test technologies misclassified for
    % different training technology subsets:
```

```
    num_min_avg_misclassified.(TLC_stages{stage}) = sum(
        statistically_significant_subsets_sorted.(TLC_stages{stage}) == min(
        statistically_significant_subsets_sorted.(TLC_stages{stage})));
    statistically_significant_subsets_min_avg_misclassified.(TLC_stages{
        stage}) = statistically_significant_subsets.(TLC_stages{stage})(
        statistically_significant_subsets_rank.(TLC_stages{stage})(1:
        num_min_avg_misclassified.(TLC_stages{stage})));

    % Locate the top 10% of statistically significant patent indicator
    % subsets:
    if total_num_statistically_significant_indicator_subsets.(TLC_stages{
        stage}) > 0
         statistically_significant_subsets_top_ten_percent.(TLC_stages{stage
            }) = statistically_significant_subsets.(TLC_stages{stage})(
            statistically_significant_subsets_rank.(TLC_stages{stage})(1:
            ceil(0.1 * total_num_statistically_significant_indicator_subsets
            .(TLC_stages{stage}))));
    end
end

%% Plot histograms based on best performing cross-validated patent
    indicator subsets:

% Evaluate each TLC stage separately:
for stage = 1:numel(TLC_stages)
    % Plot a histogram of the most frequently occuring indicators in
    % identified best patent indicator subsets:
    figure_name = ['Histogram of most frequently occuring patent indicators
         in best performing cross-validated patent indicator subsets - ',
        TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    hold on;
    histogram([statistically_significant_subsets_min_avg_misclassified.(
        TLC_stages{stage}){1:end}]);

    % Add title, X, and Y labels to figure:
    title(figure_name);
    xlabel('Patent indicator','FontSize',12)
    ylabel('Count','FontSize',12)

    % Save figure:
    saveas(gcf,figure_name,'fig');
    hold off;
```

```
    if total_num_statistically_significant_indicator_subsets.(TLC_stages{
        stage}) > 0
        % Plot a histogram of the most frequently occuring indicators in
        % identified best patent indicator subsets:
        figure_name = ['Histogram of most frequently occuring patent
            indicators in top ten percent of statisically significant cross-
            validated subsets - ',TLC_stages{stage}];
        figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1,
            1, scrsz(3), scrsz(4)]);
        hold on;
        histogram([statistically_significant_subsets_top_ten_percent.(
            TLC_stages{stage}){1:end}]);

        % Add title, X, and Y labels to figure:
        title(figure_name);
        xlabel('Patent indicator','FontSize',12)
        ylabel('Count','FontSize',12)

        % Save figure:
        saveas(gcf,figure_name,'fig');
        hold off;
    end
end

%% Save all variables to a MAT file:
save('statistical_analysis.mat');

%% Return to the patent data folder:

cd(patent_data_path)

toc()

%% Generate spectrograms for each of the patent indicator curves generated
    for each technology considered:

% for i = 1:numel(technology)
%     % Select the current indicator set for analysis:
%     current_technology_data = technology_data_filtered.data.(technology{i
    });
%
%     % Extract the normalised time values for the current technology:
%     normalised_time = current_technology_data(:,17);
%
%     % Iterate through each of the different patent indicators and plot a
%     % spectrogram (NB: there are currently 10 patent indicators used in
```

```
%     % this analysis, plus technology life cycle stages, so if any new
%     % indicators where to be added the number of cycles below would need to
%     % be adjusted to match):
%     for j = 1:max_num_indicators
%         % Select the current indicator to plot for the current technology:
%         normalised_indicator = current_technology_data(:,17 + j);
%
%         % Create new figure for each spectrogram:
%         figure(j)
%
%         % Create the spectrogram plot:
%         spectrogram(normalised_indicator)
%     end
%
% end
%
% toc()
```

Listing 5: functional_data_analysis.m

```
% This script is used to conduct functional data analysis (as an extension
% of the statistical analysis conducted using the
% 'statistical_analysis_segmented_clustering.m' file) on each of the patent
% indicators and patent indicator sets extracted for each technology using
% the 'extract_patent_metrics.m' script, which have subsequently been
% compiled in the 'Extracted patent indicators.xlsx' spreadsheet.

clearvars
clear all
close all

tic()

% Load the results and variables used in the already completed statistical
% analysis:
load('statistical_analysis.mat');

% Specify the Technology Life Cycle stage to consider during this
% functional data analysis process:
% 1 = all TLC stages
% 2 = emergence
% 3 = growth
% 4 = maturity
% 5 = decline
stage = 2;

% Specify patent indicator subset to use for model building purposes from
% list of top performing indicator subsets identified from 'leave-half-out'
% and/or 'leave-one-out' cross-validation analysis:
model_indicator_subset = [4,6];
% model_indicator_subset = [6,7];
% model_indicator_subset = [3,9];

% Option to use aligned or unaligned time signals (1 = aligned, 0 =
% unaligned)
signal_alignment = 0;

% Specify order of B-splines to use in basis functions:
bspline_order = 6;

% Preallocate empty cell array for storing names of dimension labels:
technology_fdnames = cell(1,3);
technology_labels = cell(1,2);
patent_indicator_labels = cell(1,2);

```

```
% Assign label names to the problem dimensions considered (see section
% 4.1.2 of 'Functional Data Analysis with R and MATLAB.pdf'):
technology_labels{1} = 'Technology';
technology_labels{2} = technology.(TLC_stages{stage});
patent_indicator_labels{1} = 'Patent indicator';
patent_indicator_labels{2} = patent_indicator_column_names;
technology_fdnames{1} = 'Time (years)';
technology_fdnames{2} = technology_labels;
technology_fdnames{3} = patent_indicator_labels;

% Set figures generated to be invisible by default:
set(0,'DefaultFigureVisible','off')

% Determine screensize so that figures are scaled to the right size for the
% current monitor (scrsz == screen size vector [left, bottom, width,
% height])
scrsz = get(0,'ScreenSize');

% Preallocate empty double and cell arrays for storing medoid alignment
% data:
model_medoid_locations_idx.(TLC_stages{stage}) = zeros(num_clusters,numel(
    model_indicator_subset));
model_realigned_cluster_ID.(TLC_stages{stage}) = zeros(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
model_cluster_labels.(TLC_stages{stage}) = zeros(num_clusters,numel(
    model_indicator_subset));
medoid_technology_mapping.(TLC_stages{stage}) = zeros(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
model_warping_paths_A_B.(TLC_stages{stage}) = cell(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
model_warping_paths_B_A.(TLC_stages{stage}) = cell(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
medoid_aligned_signals.(TLC_stages{stage}) = cell(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
unaligned_signals.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{
    stage})),numel(model_indicator_subset));
medoid_aligned_time_normalised_signals.(TLC_stages{stage}) = cell(numel(
    technology.(TLC_stages{stage})),numel(model_indicator_subset));
unaligned_time_normalised_signals.(TLC_stages{stage}) = cell(numel(
    technology.(TLC_stages{stage})),numel(model_indicator_subset));

% Preallocate empty cell arrays for storing functional data constructs:
functional_basis_object.(TLC_stages{stage}) = cell(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
functional_parameter_object.(TLC_stages{stage}) = cell(numel(technology.(
    TLC_stages{stage})),numel(model_indicator_subset));
```

```
technology_FDO.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_df.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_gcv.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_beta.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_SSE.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_penmat.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_y2cMap.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_WFD.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
technology_FSTR.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
time_normalised_values.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages{stage})),numel(model_indicator_subset));
mean_technology_values.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
mean_technology_function.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
patent_indicator_functional_basis_object.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_functional_parameter_object.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_FDO.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_df.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_gcv.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_beta.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_SSE.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_penmat.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_y2cMap.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_WFD.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
patent_indicator_FSTR.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
```

```
%% Build functional models of the technology profiles mapped to each patent
    indicator included in subset selected for model building purposes

% Build functional models of the technology profiles mapped to each patent
% indicator included in subset selected for model building purposes:
for i = 1:numel(model_indicator_subset)
    % Select the current component of the selected model indicator subset:
    model_component = model_indicator_subset(i);

    % Extract medoid indices, realigned cluster IDs, and group labels
    % corresponding to the current component of the selected model
    % indicator subset:
    model_medoid_locations_idx.(TLC_stages{stage})(:,i) =
        medoid_locations_idx_subset.(TLC_stages{stage})(:,model_component);
    model_realigned_cluster_ID.(TLC_stages{stage})(:,i) =
        realigned_cluster_ID_subsets.(TLC_stages{stage})(:,model_component);
    model_cluster_labels.(TLC_stages{stage})(:,i) =
        model_realigned_cluster_ID.(TLC_stages{stage})(
        model_medoid_locations_idx.(TLC_stages{stage})(:,i),i);

    % Map medoid technology indices across to realigned cluster IDs:
    medoid_technology_mapping.(TLC_stages{stage})(:,i) =
        model_realigned_cluster_ID.(TLC_stages{stage})(:,i);
    for j = 1:num_clusters
        medoid_technology_mapping.(TLC_stages{stage})(
            medoid_technology_mapping.(TLC_stages{stage})(:,i) ==
            model_cluster_labels.(TLC_stages{stage})(j,i),i) =
            model_medoid_locations_idx.(TLC_stages{stage})(j,i);
    end

    % Generate figure for plotting aligned technology time series clusters:
    if signal_alignment == 1
        figure_name = ['Medoid aligned technology profiles for ',
            patent_indicator_column_names{model_component},' - ',TLC_stages{
            stage}];
    else
        figure_name = ['Technology profiles for ',
            patent_indicator_column_names{model_component},' - ',TLC_stages{
            stage}];
    end
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    hold on

    % Use medoid technology mapping to select the Dynamic Time Warping
```

```
    % paths that align each technology to its respective cluster:
    for j = 1:numel(technology.(TLC_stages{stage}))
        % Select the current indicator set for analysis:
        current_technology_data = technology_data_filtered.(TLC_stages{
            stage}).(technology.(TLC_stages{stage}){j});

        % Select the Dynamic Time Warping path for the current technology
        % and medoid alignment:
        model_warping_paths_A_B.(TLC_stages{stage}){j,i} =
            current_technology_warping_path.(TLC_stages{stage}){j,
            medoid_technology_mapping.(TLC_stages{stage})(j,i),
            model_component};
        model_warping_paths_B_A.(TLC_stages{stage}){j,i} =
            comparison_technology_warping_path.(TLC_stages{stage}){j,
            medoid_technology_mapping.(TLC_stages{stage})(j,i),
            model_component};

        % Compile matrices of medoid aligned and unaligned signals:
        medoid_aligned_signals.(TLC_stages{stage}){j,i} = [
            model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:),
            current_technology_data(model_warping_paths_A_B.(TLC_stages{
            stage}){j,i}(:),model_component)];
        unaligned_signals.(TLC_stages{stage}){j,i} = [(1:size(
            current_technology_data,1))',current_technology_data(:,
            model_component)];

        % Compile matrices of medoid aligned and unaligned time normalised
        % signals:
        medoid_aligned_time_normalised_signals.(TLC_stages{stage}){j,i} = [
            model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:)/max(
            model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:)),
            current_technology_data(model_warping_paths_A_B.(TLC_stages{
            stage}){j,i}(:),model_component)];
        unaligned_time_normalised_signals.(TLC_stages{stage}){j,i} = [(1:
            size(current_technology_data,1))'/size(current_technology_data
            ,1),current_technology_data(:,model_component)];

        % Plot the medoid aligned technologies for the current component of
        % the selected modelling indicator subset:
        if model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 1
            % Plot the medoid aligned technology profiles without any
            % further time normalisation:
            if signal_alignment == 1
                subplot(2,1,1), plot(model_warping_paths_B_A.(TLC_stages{
                    stage}){j,i}(:),current_technology_data(
```

```
                model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                model_component),'r-');
        else
            subplot(2,1,1), plot(unaligned_signals.(TLC_stages{stage}){
                j,i}(:,1),unaligned_signals.(TLC_stages{stage}){j,i
                }(:,2),'r-');
        end
        hold on

        % Add title, X, and Y labels to subplot:
        if signal_alignment == 1
            title([figure_name,' (medoid aligned time)']);
        else
            title([figure_name,' (real-time)']);
        end
        xlabel('Time (years)','FontSize',12)
        ylabel('Normalised IHS indicator count','FontSize',12)

        % Plot the medoid aligned and time normalised technology
        % profiles:
        if signal_alignment == 1
            subplot(2,1,2), plot(model_warping_paths_B_A.(TLC_stages{
                stage}){j,i}(:)/max(model_warping_paths_B_A.(TLC_stages{
                stage}){j,i}(:)),current_technology_data(
                model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                model_component),'r-');
        else
            subplot(2,1,2), plot(unaligned_time_normalised_signals.(
                TLC_stages{stage}){j,i}(:,1),
                unaligned_time_normalised_signals.(TLC_stages{stage}){j,
                i}(:,2),'r-');
        end
        hold on

        % Add title, X, and Y labels to subplot:
        if signal_alignment == 1
            title([figure_name,' (normalised medoid aligned time)']);
        else
            title([figure_name,' (normalised time)']);
        end
        xlabel('Normalised time','FontSize',12)
        ylabel('Normalised IHS indicator count','FontSize',12)

    elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 2
        % Plot the medoid aligned technology profiles without any
        % further time normalisation:
```

```
        if signal_alignment == 1
            subplot(2,1,1), plot(model_warping_paths_B_A.(TLC_stages{
                stage}){j,i}(:),current_technology_data(
                model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                model_component),'b-');
        else
            subplot(2,1,1), plot(unaligned_signals.(TLC_stages{stage}){
                j,i}(:,1),unaligned_signals.(TLC_stages{stage}){j,i
                }(:,2),'b-');
        end
        hold on

        % Add title, X, and Y labels to subplot:
        if signal_alignment == 1
            title([figure_name,' (medoid aligned time)']);
        else
            title([figure_name,' (real-time)']);
        end
        xlabel('Time (years)','FontSize',12)
        ylabel('Normalised IHS indicator count','FontSize',12)

        % Plot the medoid aligned and time normalised technology
        % profiles:
        if signal_alignment == 1
            subplot(2,1,2), plot(model_warping_paths_B_A.(TLC_stages{
                stage}){j,i}(:)/max(model_warping_paths_B_A.(TLC_stages{
                stage}){j,i}(:)),current_technology_data(
                model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                model_component),'b-');
        else
            subplot(2,1,2), plot(unaligned_time_normalised_signals.(
                TLC_stages{stage}){j,i}(:,1),
                unaligned_time_normalised_signals.(TLC_stages{stage}){j,
                i}(:,2),'b-');
        end
        hold on

        % Add title, X, and Y labels to subplot:
        if signal_alignment == 1
            title([figure_name,' (normalised medoid aligned time)']);
        else
            title([figure_name,' (normalised time)']);
        end
        xlabel('Normalised time','FontSize',12)
        ylabel('Normalised IHS indicator count','FontSize',12)
```

```
        elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 3
            % Plot the medoid aligned technology profiles without any
            % further time normalisation:
            if signal_alignment == 1
                subplot(2,1,1), plot(model_warping_paths_B_A.(TLC_stages{
                    stage}){j,i}(:),current_technology_data(
                    model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                    model_component),'g-');
            else
                subplot(2,1,1), plot(unaligned_signals.(TLC_stages{stage}){
                    j,i}(:,1),unaligned_signals.(TLC_stages{stage}){j,i
                    }(:,2),'g-');
            end
            hold on

            % Add title, X, and Y labels to subplot:
            if signal_alignment == 1
                title([figure_name,' (medoid aligned time)']);
            else
                title([figure_name,' (real-time)']);
            end
            xlabel('Time (years)','FontSize',12)
            ylabel('Normalised IHS indicator count','FontSize',12)

            % Plot the medoid aligned and time normalised technology
            % profiles:
            if signal_alignment == 1
                subplot(2,1,2), plot(model_warping_paths_B_A.(TLC_stages{
                    stage}){j,i}(:)/max(model_warping_paths_B_A.(TLC_stages{
                    stage}){j,i}(:)),current_technology_data(
                    model_warping_paths_A_B.(TLC_stages{stage}){j,i}(:),
                    model_component),'g-');
            else
                subplot(2,1,2), plot(unaligned_time_normalised_signals.(
                    TLC_stages{stage}){j,i}(:,1),
                    unaligned_time_normalised_signals.(TLC_stages{stage}){j,
                    i}(:,2),'g-');
            end
            hold on

            % Add title, X, and Y labels to subplot:
            if signal_alignment == 1
                title([figure_name,' (normalised medoid aligned time)']);
            else
                title([figure_name,' (normalised time)']);
            end
```

```
            xlabel('Normalised time','FontSize',12)
            ylabel('Normalised IHS indicator count','FontSize',12)
        end
    end

    % Plot the medoid time series for the current patent indicator group:
    for j = 1:num_clusters
        if signal_alignment == 1
            subplot(2,1,1), plot(model_warping_paths_B_A.(TLC_stages{stage
                }){model_medoid_locations_idx.(TLC_stages{stage})(j,i),i}(:)
                ,...
                 technology_data_filtered.(TLC_stages{stage}).(technology.(
                    TLC_stages{stage}){model_medoid_locations_idx.(
                    TLC_stages{stage})(j,i)})(model_warping_paths_A_B.(
                    TLC_stages{stage}){model_medoid_locations_idx.(
                    TLC_stages{stage})(j,i),i}(:),model_component),'co','
                    MarkerSize',7,'LineWidth',1.5);
            subplot(2,1,2), plot((1:numel(model_warping_paths_B_A.(
                TLC_stages{stage}){model_medoid_locations_idx.(TLC_stages{
                stage})(j,i),i}(:)))/max(model_warping_paths_A_B.(TLC_stages
                {stage}){model_medoid_locations_idx.(TLC_stages{stage})(j,i)
                ,i}(:)),...
                 technology_data_filtered.(TLC_stages{stage}).(technology.(
                    TLC_stages{stage}){model_medoid_locations_idx.(
                    TLC_stages{stage})(j,i)})(model_warping_paths_A_B.(
                    TLC_stages{stage}){model_medoid_locations_idx.(
                    TLC_stages{stage})(j,i),i}(:),model_component),'co','
                    MarkerSize',7,'LineWidth',1.5);
        else
            subplot(2,1,1), plot(unaligned_signals.(TLC_stages{stage}){
                model_medoid_locations_idx.(TLC_stages{stage})(j,i),i}(:,1)
                ,...
                 unaligned_signals.(TLC_stages{stage}){
                    model_medoid_locations_idx.(TLC_stages{stage})(j,i),i
                    }(:,2),'co','MarkerSize',7,'LineWidth',1.5);
            subplot(2,1,2), plot(unaligned_time_normalised_signals.(
                TLC_stages{stage}){model_medoid_locations_idx.(TLC_stages{
                stage})(j,i),i}(:,1),...
                 unaligned_time_normalised_signals.(TLC_stages{stage}){
                    model_medoid_locations_idx.(TLC_stages{stage})(j,i),i
                    }(:,2),'co','MarkerSize',7,'LineWidth',1.5);
        end
    end

    % Add legend to the technology time series clusters:
```

```
    legend(strrep(technology.(TLC_stages{stage}),'_',' '),'FontSize',12,'
        Location','northwest');

    % Set figures to be visible when opened later:
    set(gcf,'CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off

    % Determine the max number of sampling points from the different
    % technology profiles for the current model component:
    if signal_alignment == 1
        num_resample_points.(TLC_stages{stage}) = max(max(cellfun(@numel,
            model_warping_paths_A_B.(TLC_stages{stage}))));
    else
        num_resample_points.(TLC_stages{stage}) = max(max(cellfun(@numel,
            unaligned_signals.(TLC_stages{stage}))/2));
    end

    for j = 1:numel(technology.(TLC_stages{stage}))
        % Select the current indicator set for analysis:
        current_technology_data = technology_data_filtered.(TLC_stages{
            stage}).(technology.(TLC_stages{stage}){j});

        % Create b-spline basis system of functional datasets. The time
        % intervals used (defined in the function/help file as 'rangeval',
        % and specified by a lower and upper time limit) are taken from
        % real-world time periods rather than normalised times (i.e.
        % between 0 and 1), to ensure that the length of each spline
        % subinterval is equal to 1, avoiding any rounding errors when
        % using large numbers of spline basis functions (see section 3.3.5
        % of 'Functional Data Analysis with R and MATLAB.pdf'). As such,
        % the upper time limit is taken as the total duration (in years) of
        % the technology dataset being considered, which is potentially
        % equal to the number of annual observations for the technology
        % concerned (i.e. size(current_technology_data,1)) since patent
        % records are provided on an annual basis anyway. This means that
        % each spline subinterval will be equal to one year:
        if signal_alignment == 1
            tvec.(TLC_stages{stage}) = medoid_aligned_signals.(TLC_stages{
                stage}){j,i}(:,1);
        else
            tvec.(TLC_stages{stage}) = unaligned_signals.(TLC_stages{stage
                }){j,i}(:,1);
        end
```

```
%         functional_basis_object.(TLC_stages{stage}){j,i} =
    create_bspline_basis([1,max(tvec.(TLC_stages{stage}))],(max(tvec.(
    TLC_stages{stage})) - 2 + bspline_order),bspline_order,tvec.(TLC_stages{
    stage}));
%         functional_basis_object.(TLC_stages{stage}){j,i} =
    create_bspline_basis([min(tvec.(TLC_stages{stage})),max(tvec.(TLC_stages
    {stage}))],(numel(tvec.(TLC_stages{stage})) - 2 + bspline_order),
    bspline_order,tvec.(TLC_stages{stage}));
        functional_basis_object.(TLC_stages{stage}){j,i} =
            create_bspline_basis([min(tvec.(TLC_stages{stage})),max(tvec.(
            TLC_stages{stage}))],(max(tvec.(TLC_stages{stage})) - 2 +
            bspline_order),bspline_order);

        % Create a Functional Parameter Object (FPO) that penalises the
        % roughness of growth of acceleration by using the fourth
        % derivative in the roughness penalty. The smoothing parameter,
        % lambda, is set to 0.01 here based on the growth curves considered
        % in section 5.2.4 of 'Functional Data Analysis with R and
        % MATLAB.pdf'. This enables smoothness to be imposed on estimated
        % functional parameters (see section 5.2.4 of 'Functional Data
        % Analysis with R and MATLAB.pdf'). Aim is to smooth the data using
        % a very light smoothing procedure (using many basis functions and
        % no or a very small penalty parameter) and use these smoothed
        % curves for my analysis:
        functional_parameter_object.(TLC_stages{stage}){j,i} = fdPar(
            functional_basis_object.(TLC_stages{stage}){j,i},4,0.01);

        % Plot the B-spline basis functions:
        figure_name = ['Functional basis system for ',technology.(
            TLC_stages{stage}){j},' based on ',patent_indicator_column_names
            {model_component},' - ',TLC_stages{stage}];
        figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1,
            1, scrsz(3), scrsz(4)]);
        hold on
        plot(functional_basis_object.(TLC_stages{stage}){j,i});

        % Set plots to be invisible now, but visible when opened later:
        set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

        % Save figure:
        saveas(gcf,figure_name,'fig')
        hold off

%         figure_name = ['Functional parameter object for ',technology.(
    TLC_stages{stage}){i},' based on ',patent_indicator_column_names{
    model_component},' - ',TLC_stages{stage}];
```

```
%         figure('Name',figure_name,'NumberTitle','off','OuterPosition',
    [1, 1, scrsz(3), scrsz(4)]);
%         hold on
%         plot(functional_parameter_object.(TLC_stages{stage}){j,i});
%
%         % Set plots to be invisible now, but visible when opened later:
%         set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')
    ')
%
%         % Save figure:
%         saveas(gcf,figure_name,'fig')
%         hold off

        % Preallocate empty cell arrays for storing matrices of basis
        % function values, derivatives basis function values, and
        % functional data objects:
        basismatrix.(TLC_stages{stage}) = cell(numel(technology.(TLC_stages
            {stage})),numel(model_indicator_subset));
        Dbasismatrix.(TLC_stages{stage}) = cell(numel(technology.(
            TLC_stages{stage})),numel(model_indicator_subset));

        % Set up functional data objects based on current technology. First
        % set up matrices of basis function values and derivative basis
        % function values for later use in plotting and as an input into
        % regression analysis (see section 3.5 of 'Functional Data Analysis
        % with R and MATLAB.pdf'):
        basismatrix.(TLC_stages{stage}){j,i} = eval_basis(tvec.(TLC_stages{
            stage}),functional_basis_object.(TLC_stages{stage}){j,i});
        Dbasismatrix.(TLC_stages{stage}){j,i} = eval_basis(tvec.(TLC_stages
            {stage}),functional_basis_object.(TLC_stages{stage}){j,i},1);

%         % Plot the basis function values for the current technology:
%         figure_name = ['Basis function values for ',technology.(
    TLC_stages{stage}){j},' based on ',patent_indicator_column_names{
    model_component},' - ',TLC_stages{stage}];
%         figure('Name',figure_name,'NumberTitle','off','OuterPosition',
    [1, 1, scrsz(3), scrsz(4)]);
%         hold on
%         plot(basismatrix.(TLC_stages{stage}){j,i});
%
%         % Add title, X, and Y labels to figure:
%         title(figure_name);
%         xlabel('Time (years)','FontSize',12)
%         ylabel('Basis function value','FontSize',12)
%
%         % Set plots to be invisible now, but visible when opened later:
```

```
%         set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
%
%         % Save figure:
%         saveas(gcf,figure_name,'fig')
%         hold off
%
%         % Plot the derivative basis function values for the current
%         % technology:
%         figure_name = ['Derivative basis function values for ',technology.(TLC_stages{stage}){j},' based on ',patent_indicator_column_names{model_component},' - ',TLC_stages{stage}];
%         figure('Name',figure_name,'NumberTitle','off','OuterPosition',[1, 1, scrsz(3), scrsz(4)]);
%         hold on
%         plot(Dbasismatrix.(TLC_stages{stage}){j,i});
%
%         % Add title, X, and Y labels to figure:
%         title(figure_name);
%         xlabel('Time (years)','FontSize',12)
%         ylabel('Derivative basis function value','FontSize',12)
%
%         % Set plots to be invisible now, but visible when opened later:
%         set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
%
%         % Save figure:
%         saveas(gcf,figure_name,'fig')
%         hold off

        % Set up functional data objects (FDO) - see help on 'smooth_basis'
        % function for explanation of using covariates and alternative
        % decomposition methods:
        % Replications (i.e. other technologies) are used to turn 'Y'
        % into a 3D array where the first dimension corresponds to argument
        % values (classifications on a year by year basis = remain constant
        % for a fixed technology), the second to replications (i.e.
        % different technologies), and the third to variables within
        % replications (i.e. chosen indicator values to use)
        % Returned objects from the 'smooth_basis' function are:
           % FDOBJ   ... an object of class fd containing coefficients.
           % DF      ... a degrees of freedom measure.
           % GCV     ... a measure of lack of fit discounted for df.
           %                If the function is univariate, GCV is a vector
           %                containing the error  sum of squares for each
           %                function, and if the function is multivariate,
```

```
                % GCV is a NVAR by NCURVES matrix.
            % BETA    ... the regression coefficients for the covariates if
            %             supplied or empty otherwise
            % SSE     ... the error sums of squares.
            %                SSE is a vector or matrix of the same size as
            %                GCV.
            % PENMAT  ... the penalty matrix, if computed, otherwise [].
            % Y2CMAP  ... the matrix mapping the data to the coefficients.
        % Returned objects from the 'smooth_pos' function are:
            % WFD     ...  Functional data object for W.
            %              Its coefficient matrix an N by NCURVE (by NVAR)
            %              matrix (or array), depending on whether the
            %              functional observations are univariate or
            %              multivariate.
            % FSTR ...  A struct object or a cell array of struct objects,
            %           one for each curve (and each variable if functions
            %           are multivariate). Each struct object has slots:
            %                f    ... The sum of squared errors
            %                grad ... The gradient
            %                norm ... The norm of the gradient
        if signal_alignment == 1
            [technology_FDO.(TLC_stages{stage}){j,i},technology_df.(
               TLC_stages{stage}){j,i},technology_gcv.(TLC_stages{stage}){j
               ,i},technology_beta.(TLC_stages{stage}){j,i},technology_SSE
               .(TLC_stages{stage}){j,i},technology_penmat.(TLC_stages{
               stage}){j,i},technology_y2cMap.(TLC_stages{stage}){j,i}] =
               smooth_basis(tvec.(TLC_stages{stage}),medoid_aligned_signals
               .(TLC_stages{stage}){j,i}(:,2),functional_parameter_object.(
               TLC_stages{stage}){j,i},'fdnames',{technology_fdnames{1},
               technology_fdnames{2}{1},technology_fdnames{3}{1}},'method',
               'qr');
%             [technology_FDO.(TLC_stages{stage}){j,i},technology_WFD.(
   TLC_stages{stage}){j,i},technology_FSTR.(TLC_stages{stage}){j,i}] =
   smooth_pos(tvec.(TLC_stages{stage}),medoid_aligned_signals.(TLC_stages{
   stage}){j,i}(:,2),functional_parameter_object.(TLC_stages{stage}){j,i});
        else
            [technology_FDO.(TLC_stages{stage}){j,i},technology_df.(
               TLC_stages{stage}){j,i},technology_gcv.(TLC_stages{stage}){j
               ,i},technology_beta.(TLC_stages{stage}){j,i},technology_SSE
               .(TLC_stages{stage}){j,i},technology_penmat.(TLC_stages{
               stage}){j,i},technology_y2cMap.(TLC_stages{stage}){j,i}] =
               smooth_basis(tvec.(TLC_stages{stage}),unaligned_signals.(
               TLC_stages{stage}){j,i}(:,2),functional_parameter_object.(
               TLC_stages{stage}){j,i},'fdnames',{technology_fdnames{1},
               technology_fdnames{2}{1},technology_fdnames{3}{1}},'method',
               'qr');
```

```
%             [technology_FDO.(TLC_stages{stage}){j,i},technology_WFD.(
    TLC_stages{stage}){j,i},technology_FSTR.(TLC_stages{stage}){j,i}] =
    smooth_pos(tvec.(TLC_stages{stage}),unaligned_signals.(TLC_stages{stage
    }){j,i}(:,2),functional_parameter_object.(TLC_stages{stage}){j,i});
        end

        % Resample the current functional data object based on the maximum
        % number of resampling points identified previously:
        if signal_alignment == 1
            tvec_resampled.(TLC_stages{stage}) = 1:(max(
                model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:)) - 1)/(
                num_resample_points.(TLC_stages{stage}) - 1):max(
                model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:));
        else
            tvec_resampled.(TLC_stages{stage}) = 1:(max(unaligned_signals.(
                TLC_stages{stage}){j,i}(:,1)) - 1)/(num_resample_points.(
                TLC_stages{stage}) - 1):max(unaligned_signals.(TLC_stages{
                stage}){j,i}(:,1));
        end

        % Extract values from the current functional data object based on
        % the maximum number of sampling points recorded for any of the
        % technologies considered to give normalised time values:
        tvec_normalised.(TLC_stages{stage}) = 0:(1/(num_resample_points.(
            TLC_stages{stage}) - 1)):1;
        time_normalised_values.(TLC_stages{stage}){j,i} = [tvec_normalised
            .(TLC_stages{stage})', eval_fd(tvec_resampled.(TLC_stages{stage
            }),technology_FDO.(TLC_stages{stage}){j,i})];
        time_normalised_values_matrix.(TLC_stages{stage})(:,j,i) =
            time_normalised_values.(TLC_stages{stage}){j,i}(:,2);

        % Generate figure for plotting current functional data object:
        figure_name = ['Functional Data Object for ',technology.(TLC_stages
            {stage}){j},' based on ',patent_indicator_column_names{
            model_component},' - ',TLC_stages{stage}];
        figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1,
            1, scrsz(3), scrsz(4)]);
        hold on

        % Plot the current functional data object along with the original
        % medoid aligned technology profile without any further time
        % normalisation:
        if signal_alignment == 1
            if model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 1
```

```
                plot(model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:),
                    current_technology_data(model_warping_paths_A_B.(
                    TLC_stages{stage}){j,i}(:),model_component),'r-');
            elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 2
                plot(model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:),
                    current_technology_data(model_warping_paths_A_B.(
                    TLC_stages{stage}){j,i}(:),model_component),'b-');
            elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 3
                plot(model_warping_paths_B_A.(TLC_stages{stage}){j,i}(:),
                    current_technology_data(model_warping_paths_A_B.(
                    TLC_stages{stage}){j,i}(:),model_component),'g-');
            end
        else
            if model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 1
                plot(unaligned_signals.(TLC_stages{stage}){j,i}(:,1),
                    unaligned_signals.(TLC_stages{stage}){j,i}(:,2),'r-');
            elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 2
                plot(unaligned_signals.(TLC_stages{stage}){j,i}(:,1),
                    unaligned_signals.(TLC_stages{stage}){j,i}(:,2),'b-');
            elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 3
                plot(unaligned_signals.(TLC_stages{stage}){j,i}(:,1),
                    unaligned_signals.(TLC_stages{stage}){j,i}(:,2),'g-');
            end
        end
        plot(technology_FDO.(TLC_stages{stage}){j,i})
        hold on

        % Add title, X, and Y labels to subplot:
        if signal_alignment == 1
            title([figure_name,' (medoid aligned time)']);
        else
            title([figure_name,' (real-time)']);
        end
        xlabel('Time (years)','FontSize',12)
        ylabel('Normalised IHS indicator count','FontSize',12)

        % Set plots to be invisible now, but visible when opened later:
        set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

        % Save figure:
        saveas(gcf,figure_name,'fig')
        hold off
    end

    % Generate figure for plotting functional data objects:
```

```
figure_name = ['Functional Data Objects based on ',
    patent_indicator_column_names{model_component},' - ',TLC_stages{
    stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on

% Plot the medoid aligned functional data objects for each technology
% profile without any further time normalisation:
for j = 1:numel(technology.(TLC_stages{stage}))
    plot(technology_FDO.(TLC_stages{stage}){j,i});
    hold on
end

% Add title, X, and Y labels to subplot:
if signal_alignment == 1
    title([figure_name,' (medoid aligned time)']);
else
    title([figure_name,' (real-time)']);
end
xlabel('Time (years)','FontSize',12)
ylabel('Normalised IHS indicator count','FontSize',12)

% Set the x-axis limits to match the largest aligned time-scale used:
if signal_alignment == 1
    max_aligned_time_value.(TLC_stages{stage}) = max(cellfun(@max,
        model_warping_paths_B_A.(TLC_stages{stage})(:,i)));
else
    max_aligned_time_value.(TLC_stages{stage}) = max(max(cellfun(@numel
        ,unaligned_signals.(TLC_stages{stage})(:,i))/2));
end
xlim([0 max_aligned_time_value.(TLC_stages{stage})]);

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Calculate mean values of resampled curves for the current model
% component:
mean_technology_values.(TLC_stages{stage}){i} = sum(
    time_normalised_values_matrix.(TLC_stages{stage})(:,:,i),2) / numel(
    technology.(TLC_stages{stage}));
```

```
mean_technology_function.(TLC_stages{stage}){i} = [tvec_normalised.(
    TLC_stages{stage})',mean_technology_values.(TLC_stages{stage}){i}];

% Generate figure for plotting time-normalised functional data objects:
figure_name = ['Time-normalised Functional Data Objects based on ',
    patent_indicator_column_names{model_component},' - ',TLC_stages{
    stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on

% Plot the medoid aligned functional data objects for each technology
% profile without any further time normalisation:
for j = 1:numel(technology.(TLC_stages{stage}))
    if model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 1
        plot(time_normalised_values.(TLC_stages{stage}){j,i}(:,1),
            time_normalised_values.(TLC_stages{stage}){j,i}(:,2),'r-');
    elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 2
        plot(time_normalised_values.(TLC_stages{stage}){j,i}(:,1),
            time_normalised_values.(TLC_stages{stage}){j,i}(:,2),'b-');
    elseif model_realigned_cluster_ID.(TLC_stages{stage})(j,i) == 3
        plot(time_normalised_values.(TLC_stages{stage}){j,i}(:,1),
            time_normalised_values.(TLC_stages{stage}){j,i}(:,2),'g-');
    end
    hold on
end

% Plot the mean value curve for the current model component:
plot(tvec_normalised.(TLC_stages{stage})',mean_technology_values.(
    TLC_stages{stage}){i},'co--');

% Add title, X, and Y labels to subplot:
if signal_alignment == 1
    title([figure_name,' (normalised medoid aligned time)']);
else
    title([figure_name,' (normalised time)']);
end
xlabel('Normalised time','FontSize',12)
ylabel('Normalised IHS indicator count','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off
```

```
end

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Scale normalised time values to maximum length of warped time paths

% Scale normalised time values to maximum length of warped time paths,
% as if based on unit intervals (this is just to avoid rounding errors
% during the creation of the functional basis system in the next step
% (see section 3.3.5 of 'Functional Data Analysis with R and
% MATLAB.pdf'), but will subsequently use normalised time values to map
% against the final functional basis systems):
tvec_normalised_scaled.(TLC_stages{stage}) = 0:1:(num_resample_points.(
    TLC_stages{stage}) - 1);

%% Create functional basis systems for use in benchmarking performance of
    functional regression analysis

% Construct the corresponding 'Constant Basis' function for use in any
% functional regression comparisons (see section 3.4.1 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
conbasis.(TLC_stages{stage}) = create_constant_basis([min(
    tvec_normalised_scaled.(TLC_stages{stage})),max(tvec_normalised_scaled.(
    TLC_stages{stage}))]);

% Construct the corresponding 'Monomial Basis' function for use in any
% statistics benchmarking exercises (see section 3.4.2 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
monbasis.(TLC_stages{stage}) = create_monomial_basis([min(
    tvec_normalised_scaled.(TLC_stages{stage})),max(tvec_normalised_scaled.(
    TLC_stages{stage}))],4);

figure_name = ['Constant basis system for functional regression analysis -
    ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on
plot(conbasis.(TLC_stages{stage}));

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
```

```
saveas(gcf,figure_name,'fig')
hold off

figure_name = ['Monomial basis system for functional regression analysis - 
    ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on
plot(monbasis.(TLC_stages{stage}));

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Create b-spline basis system for the beta coefficient functions

% Create b-spline basis system for the beta coefficient functions. The
% time intervals used (defined in the function/help file as 'rangeval',
% and specified by a lower and upper time limit) are taken from the
% scaled normalised time periods above rather than normalised times
% (i.e. between 0 and 1), to ensure that the length of each spline
% subinterval is equal to 1, avoiding any rounding errors when using
% large numbers of spline basis functions (see section 3.3.5 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
beta_functional_basis_object.(TLC_stages{stage}) = create_bspline_basis([
    min(tvec_normalised_scaled.(TLC_stages{stage})),max(
    tvec_normalised_scaled.(TLC_stages{stage}))],(max(tvec_normalised_scaled
    .(TLC_stages{stage})) - 2 + bspline_order),bspline_order);

% Create a Functional Parameter Object (FPO) that penalises the roughness
% of growth of acceleration of each beta coefficient function by using the
% second/third/fourth/fifth/sixth/seventh derivative in the roughness
% penalty (This is equivalent to creating 'betafdPar' in section 9.4.2 of
% 'Functional Data Analysis with R and MATLAB.pdf' - see page 137). The
% smoothing parameter, lambda, was initially set to 0.01 here based on the
% growth curves considered in section 5.2.4 of 'Functional Data Analysis
% with R and MATLAB.pdf', but has since been refined based on
% 'leave-one-out' cross validation scores for different lambda values (see
% below cross-validation scores for lambda section below). This enables
% smoothness to be imposed on estimated functional parameters (see section
% 5.2.4 of 'Functional Data Analysis with R and MATLAB.pdf'). Aim is to
% smooth the data using a very light smoothing procedure (using many basis
% functions and no or a very small penalty parameter) and use these
```

```
% smoothed curves for my analysis:
if signal_alignment == 1
    beta_functional_parameter_object.(TLC_stages{stage}) = fdPar(
        beta_functional_basis_object.(TLC_stages{stage}),2,10^4.8);
else
    beta_functional_parameter_object.(TLC_stages{stage}) = fdPar(
        beta_functional_basis_object.(TLC_stages{stage}),2,10^4.8);
end

% Plot the B-spline basis functions:
figure_name = ['Functional basis system for the beta coefficients used in
    functional regression analysis - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on
plot(beta_functional_basis_object.(TLC_stages{stage}));

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Preallocate empty cell array for storing beta basis systems:
beta_basis_systems.(TLC_stages{stage}) = cell(1,(numel(
    model_indicator_subset) + 1));

% Create beta coefficient basis system cell array from constant basis
% system and b-spline basis systems (this is equivalent to the 'betalist'
% variable created on page 134, section 9.4.1 of 'Functional Data Analysis
% with R and MATLAB.pdf'). Here the constant basis system accounts for
% 'alpha', the multiplier of the constant intercept covariate set up
% as the first element in 'covariates' below (see page 134):
for i = 1:(numel(model_indicator_subset) + 1)
    if i == 1
        beta_basis_systems.(TLC_stages{stage}){i} = conbasis.(TLC_stages{
            stage});
    else
        beta_basis_systems.(TLC_stages{stage}){i} =
            beta_functional_parameter_object.(TLC_stages{stage});
    end
end

%% Build functional data object for each model component
```

```
% Generate sequence of log lambda values to evaluate smoothness fit:
log_lambda_patent_indicators.(TLC_stages{stage}) = -5:0.5:12;
number_lambda_values_patent_indicators.(TLC_stages{stage}) = length(
    log_lambda_patent_indicators.(TLC_stages{stage}));

% Preallocate empty double and cell arrays for storing degrees of freedom
% and generalised cross-validation coefficients (i.e. 'dfsave' and
% 'gcvsave' from section 5.3 of 'Functional Data Analysis with R and
% MATLAB.pdf'):
indicator_fit_df.(TLC_stages{stage}) = zeros(
    number_lambda_values_patent_indicators.(TLC_stages{stage}),numel(
    model_indicator_subset));
indicator_fit_gcv.(TLC_stages{stage}) = zeros(
    number_lambda_values_patent_indicators.(TLC_stages{stage}),numel(
    model_indicator_subset));
indicator_fit_functional_parameter_object.(TLC_stages{stage}) = cell(
    number_lambda_values_patent_indicators.(TLC_stages{stage}),numel(
    model_indicator_subset));
curve_fit_gcv.(TLC_stages{stage}) = cell(
    number_lambda_values_patent_indicators.(TLC_stages{stage}),numel(
    model_indicator_subset));

% Preallocate empty cell arrays for storing values assessing the fit of the
% functional data objects created:
patent_indicator_FDO_values.(TLC_stages{stage}) = cell(1,numel(
    model_indicator_subset));
patent_indicator_FDO_residuals.(TLC_stages{stage}) = cell(1,numel(
    model_indicator_subset));
patent_indicator_FDO_variance_across_technologies.(TLC_stages{stage}) =
    cell(1,numel(model_indicator_subset));
patent_indicator_FDO_variance_across_time.(TLC_stages{stage}) = cell(1,
    numel(model_indicator_subset));
patent_indicator_FDO_standard_deviations_line.(TLC_stages{stage}) = cell(1,
    numel(model_indicator_subset));
patent_indicator_FDO_standard_deviations_line_fit.(TLC_stages{stage}) =
    cell(1,numel(model_indicator_subset));

% Use resampled, time normalised, medoid aligned technology profiles to
% build functional data object for each model component:
for i = 1:numel(model_indicator_subset)
     % Select the current component of the selected model indicator subset:
     model_component = model_indicator_subset(i);

     % Create b-spline basis system for the current model component (i.e.
     % patent indicator), using the same time normalised functions as above:
```

```
patent_indicator_functional_basis_object.(TLC_stages{stage}){i} =
    create_bspline_basis([min(tvec_normalised_scaled.(TLC_stages{stage})
    ),max(tvec_normalised_scaled.(TLC_stages{stage}))],(max(
    tvec_normalised_scaled.(TLC_stages{stage})) - 2 + bspline_order),
    bspline_order);

% Conduct generalised cross-validation scoring of possible values of
% the smoothing parameter, lambda, to use in patent indicator
% functional parameter object for final functional regression analysis.
% This is equivalent to the example lambda generalised cross-validation
% scoring carried out in section 5.3 of 'Functional Data Analysis with
% R and MATLAB.pdf'

% Iterate through possible smoothing parameter (lambda) values for each
% patent indicator included for model building purposes and calculate
% degrees of freedom and generalised cross-validation criterion:
for j = 1:number_lambda_values_patent_indicators.(TLC_stages{stage})
     % Select current lambda value:
     lambda_patent_indicators.(TLC_stages{stage}) = 10^(
         log_lambda_patent_indicators.(TLC_stages{stage})(j));

     % Create a Functional Parameter Object (FPO) that penalises the
     % roughness of growth of acceleration by using the
     % second/third/fourth/fifth/sixth/seventh derivative in the
     % roughness penalty with the current smoothing parameter (lambda):
     indicator_fit_functional_parameter_object.(TLC_stages{stage}){j,i}
         = fdPar(patent_indicator_functional_basis_object.(TLC_stages{
         stage}){i},2,lambda_patent_indicators.(TLC_stages{stage}));
     [~,indicator_fit_df.(TLC_stages{stage})(j,i),curve_fit_gcv.(
         TLC_stages{stage}){j,i}] = smooth_basis(tvec_normalised_scaled.(
         TLC_stages{stage}),time_normalised_values_matrix.(TLC_stages{
         stage})(:,:,i),indicator_fit_functional_parameter_object.(
         TLC_stages{stage}){j,i},'method','qr');

     % Sum generalised cross-validation coefficients together for all
     % replicants included in the current patent indicator fit:
     indicator_fit_gcv.(TLC_stages{stage})(j,i) = sum(curve_fit_gcv.(
         TLC_stages{stage}){j,i});
end

% Plot the degrees of freedom for possible smoothing parameters to use
% in creating a functional parameter object for the current patent
% indicator:
figure_name = ['Degrees of freedom for functional parameter object
    smoothing parameters to fit ',patent_indicator_column_names{
    model_component},' - ',TLC_stages{stage}];
```

```
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
plot(log_lambda_patent_indicators.(TLC_stages{stage}),indicator_fit_df
    .(TLC_stages{stage})(:,i),'ro-');
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Log 10 of smoothing parameter, lambda','FontSize',12)
ylabel('Degrees of freedom','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Plot the generalised cross-validation scores for possible smoothing
% parameters to use in creating a functional parameter object for the
% current patent indicator:
figure_name = ['Generalised cross-validation scores for ',
    patent_indicator_column_names{model_component},' functional
    parameter object smoothing parameter - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
plot(log_lambda_patent_indicators.(TLC_stages{stage}),indicator_fit_gcv
    .(TLC_stages{stage})(:,i),'ro-');
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Log 10 of smoothing parameter, lambda','FontSize',12)
ylabel('Generalised cross-validation criterion value','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Create functional parameter object and functional data object for
% current model component (i.e. patent indicator), using the same time
% normalised functions as above and smoothing parameter, lambda, based
% on the generalised cross-validation criterion values plotted above
```

```
    % (NB: currently need to re-run script to adjust these values - see
    % screenshots for analysis of curves and selection of lambda values
    % used below). This enables smoothness to be imposed on estimated
    % functional parameters (see section 5.2.4 of 'Functional Data Analysis
    % with R and MATLAB.pdf'). Aim is to smooth the data using a very light
    % smoothing procedure (using many basis functions and no or a very
    % small penalty parameter) and use these smoothed curves for functional
    % regression analysis:
    if signal_alignment == 1
        patent_indicator_functional_parameter_object.(TLC_stages{stage}){i}
             = fdPar(patent_indicator_functional_basis_object.(TLC_stages{
            stage}){i},2,100);
    else
        patent_indicator_functional_parameter_object.(TLC_stages{stage}){i}
             = fdPar(patent_indicator_functional_basis_object.(TLC_stages{
            stage}){i},2,100);
    end
    [patent_indicator_FDO.(TLC_stages{stage}){i},patent_indicator_df.(
        TLC_stages{stage}){i},patent_indicator_gcv.(TLC_stages{stage}){i},
        patent_indicator_beta.(TLC_stages{stage}){i},patent_indicator_SSE.(
        TLC_stages{stage}){i},patent_indicator_penmat.(TLC_stages{stage}){i
        },patent_indicator_y2cMap.(TLC_stages{stage}){i}] = smooth_basis(
        tvec_normalised_scaled.(TLC_stages{stage}),
        time_normalised_values_matrix.(TLC_stages{stage})(:,:,i),
        patent_indicator_functional_parameter_object.(TLC_stages{stage}){i},
        'fdnames',{technology_fdnames{1},technology_fdnames{2}{1},
        technology_fdnames{3}{1}},'method','qr');
%     [patent_indicator_FDO.(TLC_stages{stage}){i},patent_indicator_WFD.(
    TLC_stages{stage}){i},patent_indicator_FSTR.(TLC_stages{stage}){i}] =
    smooth_pos(tvec_normalised_scaled.(TLC_stages{stage}),
    time_normalised_values_matrix.(TLC_stages{stage})(:,:,i),
    patent_indicator_functional_parameter_object.(TLC_stages{stage}){i});

    % Plot the medoid and time normalised functional data object for the
    % current patent indicator:
    figure_name = ['Functional Data Object for all technology profiles
        based on ',patent_indicator_column_names{model_component},' - ',
        TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    plot(patent_indicator_FDO.(TLC_stages{stage}){i});
    hold on

    % Add title, X, and Y labels to subplot:
    if signal_alignment == 1
        title([figure_name,' (normalised medoid aligned time)']);
```

```
    else
        title([figure_name,' (normalised time)']);
    end
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel('Normalised IHS indicator count','FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off

    % Assess the fit of the functional data object to the current patent
    % indicator technology profile set (see section 5.5 of 'Functional Data
    % Analysis with R and MATLAB.pdf'):
    patent_indicator_FDO_values.(TLC_stages{stage}){i} = eval_fd(
        tvec_normalised_scaled.(TLC_stages{stage}),patent_indicator_FDO.(
        TLC_stages{stage}){i});
    patent_indicator_FDO_residuals.(TLC_stages{stage}){i} =
        time_normalised_values_matrix.(TLC_stages{stage})(:,:,i) -
        patent_indicator_FDO_values.(TLC_stages{stage}){i};

    % Create variance vectors for the current patent indicator functional
    % data object to determine variance across the technologies considered,
    % and across the normalised time period considered (see section 5.5 of
    % 'Functional Data Analysis with R and MATLAB.pdf'):
    patent_indicator_FDO_variance_across_technologies.(TLC_stages{stage}){i
        } = sum((patent_indicator_FDO_residuals.(TLC_stages{stage}){i})
        .^2,2) / numel(technology.(TLC_stages{stage}));
    patent_indicator_FDO_variance_across_time.(TLC_stages{stage}){i} = sum
        ((patent_indicator_FDO_residuals.(TLC_stages{stage}){i}).^2,1) / (
        size(patent_indicator_FDO_residuals.(TLC_stages{stage}){i},1) -
        patent_indicator_df.(TLC_stages{stage}){i});

    % Plot the variation in residuals within the technologies considered
    % within the current patent indicator functional data object. The
    % standard deviation is used for this as in section 5.5 of 'Functional
    % Data Analysis with R and MATLAB.pdf':
    figure_name = ['Standard deviations of the residuals within
        technologies from the functional data object for ',
        patent_indicator_column_names{model_component},' - ',TLC_stages{
        stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
```

```
plot(1:numel(technology.(TLC_stages{stage})),sqrt(
    patent_indicator_FDO_variance_across_time.(TLC_stages{stage}){i}),'
    bo');
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Technology','FontSize',12)
ylabel('Standard deviation across normalised and scaled time','FontSize
    ',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Create functional data object to represent the smoothed log of the
% standard deviations for plotting the variation in residuals within
% the normalised and scaled time period (see section 5.5 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
patent_indicator_FDO_standard_deviations_line.(TLC_stages{stage}){i} =
    smooth_basis(tvec_normalised_scaled.(TLC_stages{stage}),log(
    patent_indicator_FDO_variance_across_technologies.(TLC_stages{stage
    }){i})/2,patent_indicator_functional_parameter_object.(TLC_stages{
    stage}){i},'method','qr');

% Exponentiating the standard deviation functional data object for
% plotting purposes (see section 5.5 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
patent_indicator_FDO_standard_deviations_line_fit.(TLC_stages{stage}){i
    } = exp(eval_fd(tvec_normalised_scaled.(TLC_stages{stage}),
    patent_indicator_FDO_standard_deviations_line.(TLC_stages{stage}){i
    }));

% Plot the variation in residuals within the normalised and scaled time
% considered within the current patent indicator functional data
% object. The standard deviation is used for this as in section 5.5 of
% 'Functional Data Analysis with R and MATLAB.pdf':
figure_name = ['Standard deviations of the residuals within time from
    the functional data object for ',patent_indicator_column_names{
    model_component},' - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on
```

```
    plot(tvec_normalised_scaled.(TLC_stages{stage}),sqrt(patent_indicator_FDO_variance_across_technologies.(TLC_stages{stage}){i}),'bo');
    line(tvec_normalised_scaled.(TLC_stages{stage}),patent_indicator_FDO_standard_deviations_line_fit.(TLC_stages{stage}){i},'Color','r', 'LineStyle','-');

    % Add title, X, and Y labels to subplot:
    title(figure_name);
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel('Standard deviation across technologies','FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off
end

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Calculate functional descriptive statistics

% Preallocate empty cell arrays for storing functional descriptive
% statistics data:
patent_indicator_FDO_mean.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
patent_indicator_FDO_standard_deviation.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
patent_indicator_bivariate_functional_data_object.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
patent_indicator_bivariate_function_values.(TLC_stages{stage}) = cell(1,numel(model_indicator_subset));
cross_covariance_bivariate_functional_data_object.(TLC_stages{stage}) = cell(numel(model_indicator_subset),numel(model_indicator_subset));
cross_covariance_bivariate_function_values.(TLC_stages{stage}) = cell(numel(model_indicator_subset),numel(model_indicator_subset));
cross_correlation_matrix.(TLC_stages{stage}) = cell(numel(model_indicator_subset),numel(model_indicator_subset));

% Cycle through eacah patent indicator included in the model:
for i = 1:numel(model_indicator_subset)
```

```
    % Select the current component of the selected model indicator subset:
    model_component = model_indicator_subset(i);

    % Calculate the functional mean and standard deviations of the current
    % patent indicator technology profile set:
    patent_indicator_FDO_mean.(TLC_stages{stage}){i} = mean(
        patent_indicator_FDO.(TLC_stages{stage}){i});
    patent_indicator_FDO_standard_deviation.(TLC_stages{stage}){i} = std_fd
        (patent_indicator_FDO.(TLC_stages{stage}){i});

    % Calculate the bivariate covariance function for curve values of the
    % current patent indicator functional data object in order to determine
    % the covariance between curves:
    patent_indicator_bivariate_functional_data_object.(TLC_stages{stage}){i
        } = var_fd(patent_indicator_FDO.(TLC_stages{stage}){i});
    patent_indicator_bivariate_function_values.(TLC_stages{stage}){i} =
        eval_bifd(tvec_normalised_scaled.(TLC_stages{stage}),
        tvec_normalised_scaled.(TLC_stages{stage}),
        patent_indicator_bivariate_functional_data_object.(TLC_stages{stage
        }){i});

    % Generate bivariate variance-covariance surface and contour plots for
    % the current patent indicator functional data object (see section
    % 6.1.1 of 'Functional Data Analysis with R and MATLAB.pdf'):
    figure_name = ['Estimated bivariate variance-covariance surface and
        contours for ',patent_indicator_column_names{model_component},' - ',
        TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    subplot(1,2,1), surf(tvec_normalised_scaled.(TLC_stages{stage}),
        tvec_normalised_scaled.(TLC_stages{stage}),
        patent_indicator_bivariate_function_values.(TLC_stages{stage}){i});
    hold on

    % Add title, X, Y, and Z labels to subplot:
    title(['Estimated bivariate variance-covariance surface for ',
        patent_indicator_column_names{model_component}]);
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel('Normalised time (scaled)','FontSize',12)
    zlabel('Variance','FontSize',12)

    subplot(1,2,2), contour(tvec_normalised_scaled.(TLC_stages{stage}),
        tvec_normalised_scaled.(TLC_stages{stage}),
        patent_indicator_bivariate_function_values.(TLC_stages{stage}){i});
    hold on

```

```
% Add title, X, and Y labels to subplot:
title(['Estimated bivariate variance-covariance contours for ',
    patent_indicator_column_names{model_component}]);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Normalised time (scaled)','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

for j = 1:numel(model_indicator_subset)
    % Calculate the bivariate cross-covariance and cross-correlation
    % functions for curve values between the current patent indicator
    % functional data object and all other patent indicator functional
    % data objects in order to determine the cross-covariance between
    % indicators:
    if i <= j
        cross_covariance_bivariate_functional_data_object.(TLC_stages{
            stage}){i,j} = var_fd(patent_indicator_FDO.(TLC_stages{stage
            }){i},patent_indicator_FDO.(TLC_stages{stage}){j});
        cross_covariance_bivariate_function_values.(TLC_stages{stage}){
            i,j} = eval_bifd(tvec_normalised_scaled.(TLC_stages{stage}),
            tvec_normalised_scaled.(TLC_stages{stage}),
            cross_covariance_bivariate_functional_data_object.(
            TLC_stages{stage}){i,j});
        cross_correlation_matrix.(TLC_stages{stage}){i,j} = cor_fd(
            tvec_normalised_scaled.(TLC_stages{stage}),
            patent_indicator_FDO.(TLC_stages{stage}){i},
            tvec_normalised_scaled.(TLC_stages{stage}),
            patent_indicator_FDO.(TLC_stages{stage}){j});

        % Generate bivariate cross-covariance surface and contour plots
        % for the current pair of patent indicator functional data
        % objects (see section 6.1.1 of 'Functional Data Analysis with
        % R and MATLAB.pdf'):
        figure_name = ['Estimated bivariate cross-covariance surface
            and contours for patent indicators ',num2str(
            model_indicator_subset(i)),' and ',num2str(
            model_indicator_subset(j)),' - ',TLC_stages{stage}];
        figure('Name',figure_name,'NumberTitle','off','OuterPosition',
            [1, 1, scrsz(3), scrsz(4)]);
        subplot(1,2,1), surf(tvec_normalised_scaled.(TLC_stages{stage})
            ,tvec_normalised_scaled.(TLC_stages{stage}),
```

```
            cross_covariance_bivariate_function_values.(TLC_stages{stage
            }){i,j});
        hold on

        % Add title, X, Y, and Z labels to subplot:
        title(['Estimated bivariate cross-covariance surface for patent
             indicators ',num2str(model_indicator_subset(i)),' and ',
            num2str(model_indicator_subset(j)),' - ',TLC_stages{stage}])
            ;
        xlabel('Normalised time (scaled)','FontSize',12)
        ylabel('Normalised time (scaled)','FontSize',12)
        zlabel('Variance','FontSize',12)

        subplot(1,2,2), contour(tvec_normalised_scaled.(TLC_stages{
            stage}),tvec_normalised_scaled.(TLC_stages{stage}),
            cross_covariance_bivariate_function_values.(TLC_stages{stage
            }){i,j});
        hold on

        % Add title, X, and Y labels to subplot:
        title(['Estimated bivariate cross-covariance contours for
            patent indicators ',num2str(model_indicator_subset(i)),' and
             ',num2str(model_indicator_subset(j)),' - ',TLC_stages{stage
            }]);
        xlabel('Normalised time (scaled)','FontSize',12)
        ylabel('Normalised time (scaled)','FontSize',12)

        % Set plots to be invisible now, but visible when opened later:
        set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on''
            )')

        % Save figure:
        saveas(gcf,figure_name,'fig')
        hold off

        % Generate bivariate cross-correlation surface and contour
        % plots for the current pair of patent indicator functional
        % data objects (see section 6.1.1 of 'Functional Data Analysis
        % with R and MATLAB.pdf'):
        figure_name = ['Estimated bivariate cross-correlation surface
            and contours for patent indicators ',num2str(
            model_indicator_subset(i)),' and ',num2str(
            model_indicator_subset(j)),' - ',TLC_stages{stage}];
        figure('Name',figure_name,'NumberTitle','off','OuterPosition',
            [1, 1, scrsz(3), scrsz(4)]);
```

```
            subplot(1,2,1), surf(tvec_normalised_scaled.(TLC_stages{stage})
                ,tvec_normalised_scaled.(TLC_stages{stage}),
                cross_correlation_matrix.(TLC_stages{stage}){i,j});
            hold on

            % Add title, X, Y, and Z labels to subplot:
            title(['Estimated bivariate cross-correlation surface for
                patent indicators ',num2str(model_indicator_subset(i)),' and
                 ',num2str(model_indicator_subset(j)),' - ',TLC_stages{stage
                }]);
            xlabel('Normalised time (scaled)','FontSize',12)
            ylabel('Normalised time (scaled)','FontSize',12)
            zlabel('Cross-correlation score','FontSize',12)

            subplot(1,2,2), contour(tvec_normalised_scaled.(TLC_stages{
                stage}),tvec_normalised_scaled.(TLC_stages{stage}),
                cross_correlation_matrix.(TLC_stages{stage}){i,j});
            hold on

            % Add title, X, and Y labels to subplot:
            title(['Estimated bivariate cross-correlation contours for
                patent indicators ',num2str(model_indicator_subset(i)),' and
                 ',num2str(model_indicator_subset(j)),' - ',TLC_stages{stage
                }]);
            xlabel('Normalised time (scaled)','FontSize',12)
            ylabel('Normalised time (scaled)','FontSize',12)

            % Set plots to be invisible now, but visible when opened later:
            set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on''
                )')

            % Save figure:
            saveas(gcf,figure_name,'fig')
            hold off
        else
            cross_covariance_bivariate_functional_data_object.(TLC_stages{
                stage}){i,j} =
                cross_covariance_bivariate_functional_data_object.(
                TLC_stages{stage}){j,i};
            cross_covariance_bivariate_function_values.(TLC_stages{stage}){
                i,j} = cross_covariance_bivariate_function_values.(
                TLC_stages{stage}){j,i};
            cross_correlation_matrix.(TLC_stages{stage}){i,j} =
                cross_correlation_matrix.(TLC_stages{stage}){j,i};
        end
    end
```

```
end

% Generate plot of the functional means of the current patent indicator
% technology profile set:
figure_name = ['Mean functional data object values for chosen patent indicator subset',' - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);
hold on
for i = 1:numel(patent_indicator_FDO_mean.(TLC_stages{stage}))
    plot(patent_indicator_FDO_mean.(TLC_stages{stage}){i});
end

% Add title, X, Y, and Z labels to subplot:
title(figure_name);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Mean normalised patent indicator count','FontSize',12)

% Add legend to the technology time series clusters:
legend(strrep(patent_indicator_labels{1, 2}(model_indicator_subset),'_',' '),'FontSize',12,'Location','northwest');

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Generate plot of the standard deviations of the current patent indicator
% technology profile set:
figure_name = ['Standard deviation of functional data objects created for chosen patent indicator subset',' - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz(3), scrsz(4)]);
hold on
for i = 1:numel(patent_indicator_FDO_standard_deviation.(TLC_stages{stage}))
    plot(patent_indicator_FDO_standard_deviation.(TLC_stages{stage}){i});
end

% Add title, X, Y, and Z labels to subplot:
title(figure_name);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Standard deviation of patent indicator FDO','FontSize',12)
```

```
% Add legend to the technology time series clusters:
legend(strrep(patent_indicator_labels{1, 2}(model_indicator_subset),'_',' '
    ),'FontSize',12,'Location','northwest');

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Examine functional covariance by applying Canonical Correlation Analysis

% Canonical Correlation Analysis (CCA) is used to examine how much
% variation is shared between the different model components (i.e. patent
% indicator technology profile sets) - see section 7.5 of 'Functional
% Data Analysis with R and MATLAB.pdf' for details.

% Create a canonical correlation analysis functional parameter object that
% has heavy penalties applied to the roughness defined by the second
% derivative of the parameter object to avoid the CCA 'greediness pitfall'
% that can make it difficult to see anything of interest in the results if
% not avoided (see page 111, section 7.5 of 'Functional Data Analysis with
% R and MATLAB.pdf'):
cca_functional_parameter_object.(TLC_stages{stage}) = fdPar(
    patent_indicator_functional_basis_object.(TLC_stages{stage}){i},2,5e6);

% Set the number of canonical weight/variable pairs that should be included
% in the analysis - "the length k of the sequence is the smallest of the
% sample size N, the number of basis functions for either functional
% variable, or the number of basis functions used for either of the probe
% weight functions" (see page 111, section 7.5 of 'Functional Data Analysis
% with R and MATLAB.pdf'). Therefore assume that the number of canonical
% weight/variable pairs is equivalent to the number of technologies:
num_canonical_pairs.(TLC_stages{stage}) = numel(technology.(TLC_stages{
    stage}));

% Preallocate empty cell array for storing results of canonical correlation
% analysis:
cca.(TLC_stages{stage}) = cell(numel(model_indicator_subset),numel(
    model_indicator_subset));
```

```
% Run canonical correlation analysis for each pair of patent indicators
% included in the model:
for i = 1:numel(model_indicator_subset)
    for j = 1:numel(model_indicator_subset)
        if i <= j
            cca.(TLC_stages{stage}){i,j} = cca_fd(patent_indicator_FDO.(
               TLC_stages{stage}){i},patent_indicator_FDO.(TLC_stages{stage
               }){j},num_canonical_pairs.(TLC_stages{stage}),
               cca_functional_parameter_object.(TLC_stages{stage}),
               cca_functional_parameter_object.(TLC_stages{stage}));

            % Plot the first type of variation associated with the first
            % canonical correlation for the current pair of patent
            % indicator functional data objects (see section 7.5 of
            % 'Functional Data Analysis with R and MATLAB.pdf'):
            figure_name = ['The first pair of canonical weight functions
               for patent indicators ',num2str(model_indicator_subset(i)),'
                and ',num2str(model_indicator_subset(j)),' - ',TLC_stages{
               stage}];
            figure('Name',figure_name,'NumberTitle','off','OuterPosition',
               [1, 1, scrsz(3), scrsz(4)]);
            hold on
            plot(cca.(TLC_stages{stage}){i,j}.wtfdx(1));
            plot(cca.(TLC_stages{stage}){i,j}.wtfdy(1));
            hold on

            % Add title and X label to subplot:
            title(figure_name);
            xlabel('Normalised time (scaled)','FontSize',12)
            hold on

            % Set plots to be invisible now, but visible when opened later:
            set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on''
               )')

            % Save figure:
            saveas(gcf,figure_name,'fig')
            hold off

            % Plot the scores for first pair of canonical variables (see
            % section 7.5 of 'Functional Data Analysis with R and
            % MATLAB.pdf'):
            figure_name = ['The scores for the first pair of canonical
               variables plotted against each other for patent indicators '
```

```
                ,num2str(model_indicator_subset(i)),' and ',num2str(
                model_indicator_subset(j)),' - ',TLC_stages{stage}];
            figure('Name',figure_name,'NumberTitle','off','OuterPosition',
                [1, 1, scrsz(3), scrsz(4)]);
            plot(cca.(TLC_stages{stage}){i,j}.varx(:,1),cca.(TLC_stages{
                stage}){i,j}.vary(:,1),'bo');
            hold on

            % Add title, X, and Y labels to subplot:
            title(figure_name);
            xlabel(['Canonical weight for patent indicator ',num2str(
                model_indicator_subset(i))],'FontSize',12)
            ylabel(['Canonical weight for patent indicator ',num2str(
                model_indicator_subset(j))],'FontSize',12)

            % Set plots to be invisible now, but visible when opened later:
            set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on''
                )')

            % Save figure:
            saveas(gcf,figure_name,'fig')
            hold off
        else
            cca.(TLC_stages{stage}){i,j} = cca.(TLC_stages{stage}){j,i};
        end
    end
end

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Create cell array of covariate functions for use in functional
    regression analysis

% Preallocate empty cell array for storing covariate functions:
covariates.(TLC_stages{stage}) = cell(1,(numel(model_indicator_subset) + 1)
    );

% Generate constant 'covariate' vector of value 1 (to be first element in
% the overall covariate matrix):
constant_covariate.(TLC_stages{stage}) = ones(numel(technology.(TLC_stages{
    stage})),1);

% Create covariates matrix combining constant covariate with medoid and
```

```
% time normalised functional data objects generated for each patent
% indicator considered in the model (this is the equivalent of the
% 'templist' cell array created on page 134, section 9.4 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
for i = 1:(numel(model_indicator_subset) + 1)
    if i == 1
        covariates.(TLC_stages{stage}){i} = constant_covariate.(TLC_stages{stage});
    else
        covariates.(TLC_stages{stage}){i} = patent_indicator_FDO.(TLC_stages{stage}){i - 1};
    end
end

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Generate plot of cross-validation scores for different values of lambda (the smoothing parameter) to use in beta basis system
%
% % This cross-validation scoring of possible values of the smoothing
% % parameter, lambda, to use in beta basis system for final functional
% % regression analysis is equivalent to the example lambda cross-validation
% % scoring carried out in section 9.4.3 of 'Functional Data Analysis with R
% % and MATLAB.pdf'
%
% % Generate sequence of log lambda values to evaluate:
% % log_lambda.(TLC_stages{stage}) = -5:1:10;
% log_lambda.(TLC_stages{stage}) = 3:0.1:8;
% % log_lambda.(TLC_stages{stage}) = 4.0;
% number_lambda_values.(TLC_stages{stage}) = length(log_lambda.(TLC_stages{stage}));
%
% % Preallocate empty double arrays for storing error sum of squares
% % cross-validation scores (i.e. SSE.CV from section 9.4.3 of 'Functional
% % Data Analysis with R and MATLAB.pdf'):
% SSE_lambda_cross_validation_score.(TLC_stages{stage}) = zeros(number_lambda_values.(TLC_stages{stage}),1);
%
% % Iterate through possible beta basis systems for each patent indicator
% % included for model building purposes with different smoothing parameter
% % (lambda) values and calculate cross-validation score:
```

```
% for j = 1:number_lambda_values.(TLC_stages{stage})
%     % Select current lambda value:
%     lambda.(TLC_stages{stage}) = 10^(log_lambda.(TLC_stages{stage})(j))
%
%     % Reset beta basis system to match default beta basis system:
%     current_beta_basis_systems = beta_basis_systems.(TLC_stages{stage});
%
%     for i = 1:numel(model_indicator_subset)
%         % Substitute current lambda value into beta basis system:
%         current_beta_basis_systems{1,i+1} = putlambda(
    current_beta_basis_systems{1,i+1},lambda.(TLC_stages{stage}));
%     end
%
%     % Compute leave-one-out cross-validated error sum of squares (SSE)
    for
%     % functional responses (see section 10.6.2 of 'Functional Data
    Analysis
%     % with R and MATLAB.pdf'):
%     current_SSE_lambda_cross_validation_score = fRegress_CV(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),current_beta_basis_systems);
%
%     % Add the current error sum of squares cross-validation score (i.e.
%     % SSE.CV from section 9.4.3 of 'Functional Data Analysis with R and
%     % MATLAB.pdf') to the corresponding array:
%     SSE_lambda_cross_validation_score.(TLC_stages{stage})(j) =
    current_SSE_lambda_cross_validation_score;
% end
%
% %% Plot the cross-validation scores for log of the smoothing parameters
    evaluated for use in the beta basis system for the current patent
    indicator
% for i = 1:numel(model_indicator_subset)
%     % Select the current component of the selected model indicator subset
    :
%     model_component = model_indicator_subset(i);
%
%     % Plot the cross-validation scores for log of the smoothing
    parameters
%     % evaluated for use in the beta basis system for the current patent
%     % indicator:
%     figure_name = ['Cross-validation scores for the ',
    patent_indicator_column_names{model_component},' beta basis system
    smoothing parameter - ',TLC_stages{stage}];
%     figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
     scrsz(3), scrsz(4)]);
```

```
%      plot(log_lambda.(TLC_stages{stage}),SSE_lambda_cross_validation_score
    .(TLC_stages{stage})(:),'ro-');
%      hold on
%
%      % Add title, X, and Y labels to subplot:
%      title(figure_name);
%      xlabel('Log 10 of smoothing parameter, lambda','FontSize',12)
%      ylabel('Cross-validation score','FontSize',12)
%
%      % Set plots to be invisible now, but visible when opened later:
%      set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
%
%      % Save figure:
%      saveas(gcf,figure_name,'fig')
%      hold off
% end

%% Run functional regression analysis using known cluster IDs, covariate
    functions, and beta basis system objects

% The functional linear model built in this section and the sections below
% are based on a set of scalar response values (Y), so are based on chapter
% 9 of 'Functional Data Analysis with R and MATLAB.pdf' (as opposed to
% chapter 10 which relates to 'Linear models for functional responses')

% Run functional regression analysis to identify functional (beta)
% coefficients (see page 137, section 9.4.2 of 'Functional Data Analysis
% with R and MATLAB.pdf') using identified smoothing parameters (see
% section 9.4.3 of 'Functional Data Analysis with R and MATLAB.pdf'):
functional_regression.(TLC_stages{stage}) = fRegress(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),beta_basis_systems.(TLC_stages{stage}));

% Extract the estimated beta functional coefficients, predicted Y values,
% and residuals from the functional regression analysis:
estimated_beta_coefficients.(TLC_stages{stage}) = functional_regression.(
    TLC_stages{stage}).betahat;
estimated_beta_coefficients_values.(TLC_stages{stage}) = cell(numel(
    estimated_beta_coefficients.(TLC_stages{stage})),1);
estimated_beta_functional_data_object.(TLC_stages{stage}) = cell(numel(
    estimated_beta_coefficients.(TLC_stages{stage})),1);
for i = 1:numel(estimated_beta_coefficients.(TLC_stages{stage}))
     estimated_beta_coefficients_values.(TLC_stages{stage}){i} = getcoef(
         estimated_beta_coefficients.(TLC_stages{stage}){i});
     estimated_beta_functional_data_object.(TLC_stages{stage}){i} = getfd(
         estimated_beta_coefficients.(TLC_stages{stage}){i});
```

```
end
predicted_values.(TLC_stages{stage}) = functional_regression.(TLC_stages{
    stage}).yhat;
residuals.(TLC_stages{stage}) = technology_data_filtered.known_cluster_id.(
    TLC_stages{stage}) - predicted_values.(TLC_stages{stage});

% Determine the variance (SigmaE_squared = SigmaE. from page 141, section
% 9.4.4 of 'Functional Data Analysis with R and MATLAB.pdf') associated
% with the functional regression fit:
SigmaE_squared.(TLC_stages{stage}) = sum(residuals.(TLC_stages{stage}).^2)
    / (numel(technology.(TLC_stages{stage})) - functional_regression.(
    TLC_stages{stage}).df);

% Create the variance matrix (i.e. SigmaE from page 141, section 9.4.4 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
SigmaE.(TLC_stages{stage}) = SigmaE_squared.(TLC_stages{stage}) * diag(ones
    (numel(technology.(TLC_stages{stage})),1));

% Plot the estimate of the constant regression coefficient:
figure_name = ['Estimated regression coefficient for the constant
    functional basis system - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
plot(estimated_beta_functional_data_object.(TLC_stages{stage}){1});
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Beta for the constant functional basis system','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Preallocate empty cell array for storing standard error estimates for
% regression coefficient functions estimated by FREGRESS:
standard_error_estimates.(TLC_stages{stage}) = cell((numel(
    estimated_beta_coefficients.(TLC_stages{stage})) - 1),1);

% Plot the estimate of the regression function for the medoid and time
% normalised functional data objects generated for each patent indicator
% considered in the model (see page 134, section 9.4.1 of 'Functional Data
```

```
% Analysis with R and MATLAB.pdf'):
for i = 1:(numel(estimated_beta_coefficients.(TLC_stages{stage})) - 1)
    % Select the current component of the selected model indicator subset:
    model_component = model_indicator_subset(i);

    % Select the corresponding matrix mapping the raw data vector 'y' to
    % the coefficient vector 'c' of the basis function expansion of 'x'
    % (see page 61, section 5.1 of 'Functional Data Analysis with R and
    % MATLAB.pdf' for explanation of y2cMap):
    current_y2cMap = patent_indicator_y2cMap.(TLC_stages{stage}){i};

    % Compute the standard error estimates for regression coefficient
    % functions estimated by FREGRESS:
    standard_error_estimates.(TLC_stages{stage}){i+1} = fRegress_stderr(
        functional_regression.(TLC_stages{stage}),current_y2cMap,SigmaE.(
        TLC_stages{stage}));

    % Extract the function curves which are plus and minus two times the
    % standard error of the regression coefficient function, to obtain the
    % approximate regression function (i.e. beta) confidence bounds:
    beta_standard_error_estimates.(TLC_stages{stage}) =
        standard_error_estimates.(TLC_stages{stage}){i+1}.betastderr;
    current_beta_standard_error_estimate = beta_standard_error_estimates.(
        TLC_stages{stage}){i+1};

    % Plot the current regression coefficient along with 95% confidence
    % bounds:
    figure_name = ['Estimated regression coefficient for predicting
        technology cluster from ',patent_indicator_column_names{
        model_component},' - ',TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    hold on
    plot(estimated_beta_functional_data_object.(TLC_stages{stage}){i+1});
    line(estimated_beta_functional_data_object.(TLC_stages{stage}){i+1}+
        times(current_beta_standard_error_estimate,2));
    line(estimated_beta_functional_data_object.(TLC_stages{stage}){i+1}-
        times(current_beta_standard_error_estimate,2));

    % Resize y-axis to fit the confidence bounds curves:
    ylim('auto');

    % Add title, X, and Y labels to subplot:
    title(figure_name);
    xlabel('Normalised time (scaled)','FontSize',12)
```

```
    ylabel(['Beta for ',patent_indicator_column_names{model_component}],'FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off
end

% Calculate R-Squared, adjusted R-Squared, and F-ratio statistics to assess
% the fit of the regression model (where 'error_sum_of_squares_Y' (or
% SSE_Y) is the total sum of squares for Y, and
% 'error_sum_of_squares_residuals' (or SSE_RES) is the total sum of squares
% for residuals) - see sections 9.4.1 and 9.4.2 of 'Functional Data
% Analysis with R and MATLAB.pdf':
error_sum_of_squares_Y.(TLC_stages{stage}) = sum((technology_data_filtered.known_cluster_id.(TLC_stages{stage}) - mean(technology_data_filtered.known_cluster_id.(TLC_stages{stage}))).^2);
error_sum_of_squares_residuals.(TLC_stages{stage}) = sum((residuals.(TLC_stages{stage})).^2);
R_squared.(TLC_stages{stage}) = (error_sum_of_squares_Y.(TLC_stages{stage}) - error_sum_of_squares_residuals.(TLC_stages{stage})) / error_sum_of_squares_Y.(TLC_stages{stage});
adjusted_R_squared.(TLC_stages{stage}) = 1 - ((1 - R_squared.(TLC_stages{stage})) * ((numel(technology.(TLC_stages{stage})) - 1) / (numel(technology.(TLC_stages{stage})) - numel(model_indicator_subset) - 1)));
degrees_freedom_1 = functional_regression.(TLC_stages{stage}).df - 1;
degrees_freedom_2 = numel(technology.(TLC_stages{stage})) - functional_regression.(TLC_stages{stage}).df;
F_ratio.(TLC_stages{stage}) = ((error_sum_of_squares_Y.(TLC_stages{stage}) - error_sum_of_squares_residuals.(TLC_stages{stage})) / degrees_freedom_1) / (error_sum_of_squares_residuals.(TLC_stages{stage}) / degrees_freedom_2);

%% Benchmark results of functional regression against regression functions obtained using a low-dimensional basis system for the beta coefficients

% Reset beta basis system to match default beta basis system:
low_dimensional_beta_basis_systems.(TLC_stages{stage}) = beta_basis_systems.(TLC_stages{stage});

% Create low-dimensional b-spline basis system for beta coefficients (see
% section 9.4.1. of 'Functional Data Analysis with R and MATLAB.pdf'):
```

```
low_dimensional_beta_functional_basis_object.(TLC_stages{stage}) =
    create_bspline_basis([min(tvec_normalised_scaled.(TLC_stages{stage})),
    max(tvec_normalised_scaled.(TLC_stages{stage}))],5);

% Substitute low-dimensional basis system into beta basis system:
for i = 1:numel(model_indicator_subset)
    low_dimensional_beta_basis_systems.(TLC_stages{stage}){1,i+1} =
        low_dimensional_beta_functional_basis_object.(TLC_stages{stage});
end

% Re-run functional regression analysis to identify functional (beta)
% coefficients (see page 134, section 9.4.1 of 'Functional Data Analysis
% with R and MATLAB.pdf') using low-dimensional basis systems for the beta
% coefficients:
low_dimensional_functional_regression.(TLC_stages{stage}) = fRegress(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),low_dimensional_beta_basis_systems.(TLC_stages{
    stage}));

% Extract the estimated beta coefficients, predicted Y values, and
% residuals when using a low-dimensional basis system for the beta
% coefficients:
low_dimensional_estimated_beta_coefficients.(TLC_stages{stage}) =
    low_dimensional_functional_regression.(TLC_stages{stage}).betahat;
low_dimensional_estimated_beta_coefficients_values.(TLC_stages{stage}) =
    cell(numel(low_dimensional_estimated_beta_coefficients.(TLC_stages{stage
    })),1);
low_dimensional_estimated_beta_functional_data_object.(TLC_stages{stage}) =
     cell(numel(low_dimensional_estimated_beta_coefficients.(TLC_stages{
    stage})),1);
for i = 1:numel(low_dimensional_estimated_beta_coefficients.(TLC_stages{
    stage}))
    low_dimensional_estimated_beta_coefficients_values.(TLC_stages{stage}){
        i} = getcoef(low_dimensional_estimated_beta_coefficients.(TLC_stages
        {stage}){i});
    low_dimensional_estimated_beta_functional_data_object.(TLC_stages{stage
        }){i} = getfd(low_dimensional_estimated_beta_coefficients.(
        TLC_stages{stage}){i});
end
low_dimensional_predicted_values.(TLC_stages{stage}) =
    low_dimensional_functional_regression.(TLC_stages{stage}).yhat;
low_dimensional_residuals.(TLC_stages{stage}) = technology_data_filtered.
    known_cluster_id.(TLC_stages{stage}) - low_dimensional_predicted_values
    .(TLC_stages{stage});

% Determine the variance (SigmaE_squared = SigmaE. from page 141, section
```

```
% 9.4.4 of 'Functional Data Analysis with R and MATLAB.pdf') associated
% with the low-dimensional functional regression fit:
low_dimensional_SigmaE_squared.(TLC_stages{stage}) = sum(
    low_dimensional_residuals.(TLC_stages{stage}).^2) / (numel(technology.(
    TLC_stages{stage})) - low_dimensional_functional_regression.(TLC_stages{
    stage}).df);

% Create the variance matrix (i.e. SigmaE from page 141, section 9.4.4 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
low_dimensional_SigmaE.(TLC_stages{stage}) = low_dimensional_SigmaE_squared
    .(TLC_stages{stage}) * diag(ones(numel(technology.(TLC_stages{stage}))
    ,1));

% Plot the low-dimensional estimate of the constant regression coefficient:
figure_name = ['Low-dimensional estimate of the regression coefficient for
    the constant functional basis system - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
plot(low_dimensional_estimated_beta_functional_data_object.(TLC_stages{
    stage}){1});
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Beta for the constant functional basis system','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Preallocate empty cell array for storing standard error estimates for the
% low dimensional regression coefficient functions estimated by FREGRESS:
low_dimensional_standard_error_estimates.(TLC_stages{stage}) = cell((numel(
    low_dimensional_estimated_beta_coefficients.(TLC_stages{stage})) - 1),1)
    ;

% Plot the estimate of the low-dimensional regression function for the
% medoid and time normalised functional data objects generated for each
% patent indicator considered in the model (see page 134, section 9.4.1 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
for i = 1:(numel(low_dimensional_estimated_beta_coefficients.(TLC_stages{
    stage})) - 1)
```

```
% Select the current component of the selected model indicator subset:
model_component = model_indicator_subset(i);

% Select the corresponding matrix mapping the raw data vector 'y' to
% the coefficient vector 'c' of the basis function expansion of 'x'
% (see page 61, section 5.1 of 'Functional Data Analysis with R and
% MATLAB.pdf' for explanation of y2cMap):
current_y2cMap = patent_indicator_y2cMap.(TLC_stages{stage}){i};

% Compute the standard error estimates for low-dimensional regression
% coefficient functions estimated by FREGRESS:
low_dimensional_standard_error_estimates.(TLC_stages{stage}){i+1} =
    fRegress_stderr(low_dimensional_functional_regression.(TLC_stages{
    stage}),current_y2cMap,low_dimensional_SigmaE.(TLC_stages{stage}));

% Extract the function curves which are plus and minus two times the
% standard error of the low-dimensional regression coefficient
% function, to obtain the approximate regression function (i.e. beta)
% confidence bounds:
low_dimensional_beta_standard_error_estimates.(TLC_stages{stage}) =
    low_dimensional_standard_error_estimates.(TLC_stages{stage}){i+1}.
    betastderr;
current_beta_standard_error_estimate =
    low_dimensional_beta_standard_error_estimates.(TLC_stages{stage}){i
    +1};

% Plot the current low-dimensional regression coefficient along with
% 95% confidence bounds:
figure_name = ['Low-dimensional estimate of the regression coefficient
    for predicting group from ',patent_indicator_column_names{
    model_component},' - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
hold on
plot(low_dimensional_estimated_beta_functional_data_object.(TLC_stages{
    stage}){i+1});
line(low_dimensional_estimated_beta_functional_data_object.(TLC_stages{
    stage}){i+1}+times(current_beta_standard_error_estimate,2));
line(low_dimensional_estimated_beta_functional_data_object.(TLC_stages{
    stage}){i+1}-times(current_beta_standard_error_estimate,2));

% Resize y-axis to fit the confidence bounds curves:
ylim('auto');

% Add title, X, and Y labels to subplot:
title(figure_name);
```

```
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel(['Beta for ',patent_indicator_column_names{model_component}],'
        FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off
end

% Calculate R-Squared, adjusted R-Squared, and F-ratio statistics to assess
% the fit of the low-dimensional basis regression model (where
% 'error_sum_of_squares_Y' (or SSE_Y) is the total sum of squares for Y,
% and 'low_dimensional_error_sum_of_squares_residuals' (or SSE_RES) is the
% total sum of squares for residuals using the low-dimensional basis system
% for beta coefficients):
low_dimensional_error_sum_of_squares_residuals.(TLC_stages{stage}) = sum((
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}) -
    low_dimensional_predicted_values.(TLC_stages{stage})).^2);
low_dimensional_R_squared.(TLC_stages{stage}) = (error_sum_of_squares_Y.(
    TLC_stages{stage}) - low_dimensional_error_sum_of_squares_residuals.(
    TLC_stages{stage})) / error_sum_of_squares_Y.(TLC_stages{stage});
low_dimensional_adjusted_R_squared.(TLC_stages{stage}) = 1 - ((1 -
    low_dimensional_R_squared.(TLC_stages{stage})) * ((numel(technology.(
    TLC_stages{stage})) - 1) / (numel(technology.(TLC_stages{stage})) -
    numel(model_indicator_subset) - 1)));
low_dimensional_degrees_freedom_1 = low_dimensional_functional_regression.(
    TLC_stages{stage}).df - 1;
low_dimensional_degrees_freedom_2 = numel(technology.(TLC_stages{stage})) -
     low_dimensional_functional_regression.(TLC_stages{stage}).df;
low_dimensional_F_ratio.(TLC_stages{stage}) = ((error_sum_of_squares_Y.(
    TLC_stages{stage}) - low_dimensional_error_sum_of_squares_residuals.(
    TLC_stages{stage})) / low_dimensional_degrees_freedom_1) / (
    low_dimensional_error_sum_of_squares_residuals.(TLC_stages{stage}) /
    low_dimensional_degrees_freedom_2);

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Benchmark results of functional regression against regression functions
    obtained using a constant basis system for beta coefficients
```

```
% Reset beta basis system to match default beta basis system:
conbasis_beta_basis_systems.(TLC_stages{stage}) = beta_basis_systems.(
    TLC_stages{stage});

% Substitute constant basis system into beta basis system:
for i = 1:numel(model_indicator_subset)
     % Substitute current lambda value into beta basis system:
     conbasis_beta_basis_systems.(TLC_stages{stage}){1,i+1} = fdPar(conbasis
         .(TLC_stages{stage}));
end

% Re-run functional regression analysis to identify functional (beta)
% coefficients (see page 137, section 9.4.2 of 'Functional Data Analysis
% with R and MATLAB.pdf') using constant basis systems for the beta
% coefficients:
conbasis_functional_regression.(TLC_stages{stage}) = fRegress(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),conbasis_beta_basis_systems.(TLC_stages{stage}));

% Extract the estimated beta coefficients and predicted Y values when using
% a constant basis system for the beta coefficients:
conbasis_estimated_beta_coefficients.(TLC_stages{stage}) =
    conbasis_functional_regression.(TLC_stages{stage}).betahat;
conbasis_estimated_beta_coefficients_values.(TLC_stages{stage}) = cell(
    numel(conbasis_estimated_beta_coefficients.(TLC_stages{stage})),1);
conbasis_estimated_beta_functional_data_object.(TLC_stages{stage}) = cell(
    numel(conbasis_estimated_beta_coefficients.(TLC_stages{stage})),1);
for i = 1:numel(conbasis_estimated_beta_coefficients.(TLC_stages{stage}))
     conbasis_estimated_beta_coefficients_values.(TLC_stages{stage}){i} =
         getcoef(conbasis_estimated_beta_coefficients.(TLC_stages{stage}){i})
         ;
     conbasis_estimated_beta_functional_data_object.(TLC_stages{stage}){i} =
          getfd(conbasis_estimated_beta_coefficients.(TLC_stages{stage}){i});
end
conbasis_predicted_values.(TLC_stages{stage}) =
    conbasis_functional_regression.(TLC_stages{stage}).yhat;

% Calculate R-Squared, adjusted R-Squared, and F-ratio statistics to assess
% the fit of the constant basis regression model (where
% 'error_sum_of_squares_Y' (or SSE_Y) is the total sum of squares for Y,
% and 'conbasis_error_sum_of_squares_residuals' (or SSE_RES) is the total
% sum of squares for residuals using the constant basis system for beta
% coefficients):
conbasis_error_sum_of_squares_residuals.(TLC_stages{stage}) = sum((
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}) -
    conbasis_predicted_values.(TLC_stages{stage})).^2);
```

```
conbasis_R_squared.(TLC_stages{stage}) = (error_sum_of_squares_Y.(
    TLC_stages{stage}) - conbasis_error_sum_of_squares_residuals.(TLC_stages
    {stage})) / error_sum_of_squares_Y.(TLC_stages{stage});
conbasis_adjusted_R_squared.(TLC_stages{stage}) = 1 - ((1 -
    conbasis_R_squared.(TLC_stages{stage})) * ((numel(technology.(TLC_stages
    {stage})) - 1) / (numel(technology.(TLC_stages{stage})) - numel(
    model_indicator_subset) - 1)));
conbasis_degrees_freedom_1 = conbasis_functional_regression.(TLC_stages{
    stage}).df - 1;
conbasis_degrees_freedom_2 = numel(technology.(TLC_stages{stage})) -
    conbasis_functional_regression.(TLC_stages{stage}).df;
conbasis_F_ratio.(TLC_stages{stage}) = ((error_sum_of_squares_Y.(TLC_stages
    {stage}) - conbasis_error_sum_of_squares_residuals.(TLC_stages{stage}))
    / conbasis_degrees_freedom_1) / (conbasis_error_sum_of_squares_residuals
    .(TLC_stages{stage}) / conbasis_degrees_freedom_2);

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Benchmark results of functional regression against regression functions
    obtained using a monomial basis system for beta coefficients

% Reset beta basis system to match default beta basis system:
monbasis_beta_basis_systems.(TLC_stages{stage}) = beta_basis_systems.(
    TLC_stages{stage});

% Substitute monomial basis system into beta basis system:
for i = 1:numel(model_indicator_subset)
     % Substitute current lambda value into beta basis system:
     monbasis_beta_basis_systems.(TLC_stages{stage}){1,i+1} = fdPar(monbasis
         .(TLC_stages{stage}));
end

% Re-run functional regression analysis to identify functional (beta)
% coefficients (see page 137, section 9.4.2 of 'Functional Data Analysis
% with R and MATLAB.pdf') using monomial basis systems for the beta
% coefficients:
monbasis_functional_regression.(TLC_stages{stage}) = fRegress(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),monbasis_beta_basis_systems.(TLC_stages{stage}));

% Extract the estimated beta coefficients, predicted Y values, and
% residuals when using a monomial basis system for the beta coefficients:
```

```
monbasis_estimated_beta_coefficients.(TLC_stages{stage}) =
    monbasis_functional_regression.(TLC_stages{stage}).betahat;
monbasis_estimated_beta_coefficients_values.(TLC_stages{stage}) = cell(
    numel(monbasis_estimated_beta_coefficients.(TLC_stages{stage})),1);
monbasis_estimated_beta_functional_data_object.(TLC_stages{stage}) = cell(
    numel(monbasis_estimated_beta_coefficients.(TLC_stages{stage})),1);
for i = 1:numel(monbasis_estimated_beta_coefficients.(TLC_stages{stage}))
     monbasis_estimated_beta_coefficients_values.(TLC_stages{stage}){i} =
         getcoef(monbasis_estimated_beta_coefficients.(TLC_stages{stage}){i})
         ;
     monbasis_estimated_beta_functional_data_object.(TLC_stages{stage}){i} =
          getfd(monbasis_estimated_beta_coefficients.(TLC_stages{stage}){i});
end
monbasis_predicted_values.(TLC_stages{stage}) =
    monbasis_functional_regression.(TLC_stages{stage}).yhat;
monbasis_residuals.(TLC_stages{stage}) = technology_data_filtered.
    known_cluster_id.(TLC_stages{stage}) - monbasis_predicted_values.(
    TLC_stages{stage});

% Determine the variance (SigmaE_squared = SigmaE. from page 141, section
% 9.4.4 of 'Functional Data Analysis with R and MATLAB.pdf') associated
% with the monomial functional regression fit:
monbasis_SigmaE_squared.(TLC_stages{stage}) = sum(monbasis_residuals.(
    TLC_stages{stage}).^2) / (numel(technology.(TLC_stages{stage})) -
    monbasis_functional_regression.(TLC_stages{stage}).df);

% Create the variance matrix (i.e. SigmaE from page 141, section 9.4.4 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
monbasis_SigmaE.(TLC_stages{stage}) = monbasis_SigmaE_squared.(TLC_stages{
    stage}) * diag(ones(numel(technology.(TLC_stages{stage})),1));

% Plot the monomial estimate of the constant regression coefficient:
figure_name = ['Monomial estimate of the regression coefficient for the
    constant functional basis system - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
plot(monbasis_estimated_beta_functional_data_object.(TLC_stages{stage}){1})
    ;
hold on

% Add title, X, and Y labels to subplot:
title(figure_name);
xlabel('Normalised time (scaled)','FontSize',12)
ylabel('Beta for the constant functional basis system','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
```

```
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

% Preallocate empty cell array for storing standard error estimates for the
% monomial regression coefficient functions estimated by FREGRESS:
monbasis_standard_error_estimates.(TLC_stages{stage}) = cell((numel(
    monbasis_estimated_beta_coefficients.(TLC_stages{stage})) - 1),1);

% Plot the estimate of the monomial regression function for the medoid and
% time normalised functional data objects generated for each patent
% indicator considered in the model (see page 134, section 9.4.1 of
% 'Functional Data Analysis with R and MATLAB.pdf'):
for i = 1:(numel(monbasis_estimated_beta_coefficients.(TLC_stages{stage}))
    - 1)
     % Select the current component of the selected model indicator subset:
     model_component = model_indicator_subset(i);

     % Select the corresponding matrix mapping the raw data vector 'y' to
     % the coefficient vector 'c' of the basis function expansion of 'x'
     % (see page 61, section 5.1 of 'Functional Data Analysis with R and
     % MATLAB.pdf' for explanation of y2cMap):
     current_y2cMap = patent_indicator_y2cMap.(TLC_stages{stage}){i};

     % Compute the standard error estimates for monomial regression
     % coefficient functions estimated by FREGRESS:
     monbasis_standard_error_estimates.(TLC_stages{stage}){i+1} =
         fRegress_stderr(monbasis_functional_regression.(TLC_stages{stage}),
         current_y2cMap,monbasis_SigmaE.(TLC_stages{stage}));

     % Extract the function curves which are plus and minus two times the
     % standard error of the monomial regression coefficient function, to
     % obtain the approximate regression function (i.e. beta) confidence
     % bounds:
     monbasis_beta_standard_error_estimates.(TLC_stages{stage}) =
         monbasis_standard_error_estimates.(TLC_stages{stage}){i+1}.
         betastderr;
     current_beta_standard_error_estimate =
         monbasis_beta_standard_error_estimates.(TLC_stages{stage}){i+1};

     % Plot the current monomial regression coefficient along with 95%
     % confidence bounds:
```

```
    figure_name = ['Monomial estimate of the regression coefficient for
        predicting group from ',patent_indicator_column_names{
        model_component},' - ',TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    hold on
    plot(monbasis_estimated_beta_functional_data_object.(TLC_stages{stage})
        {i+1});
%     line(monbasis_estimated_beta_functional_data_object.(TLC_stages{stage
    }){i+1}+times(current_beta_standard_error_estimate,2));
%     line(monbasis_estimated_beta_functional_data_object.(TLC_stages{stage
    }){i+1}-times(current_beta_standard_error_estimate,2));

    % Resize y-axis to fit the confidence bounds curves:
    ylim('auto');

    % Add title, X, and Y labels to subplot:
    title(figure_name);
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel(['Beta for ',patent_indicator_column_names{model_component}],'
        FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off
end

% Calculate R-Squared, adjusted R-Squared, and F-ratio statistics to assess
% the fit of the monomial basis regression model (where
% 'error_sum_of_squares_Y' (or SSE_Y) is the total sum of squares for Y,
% and 'conbasis_error_sum_of_squares_residuals' (or SSE_RES) is the total
% sum of squares for residuals using the constant basis system for beta
% coefficients):
monbasis_error_sum_of_squares_residuals.(TLC_stages{stage}) = sum((
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}) -
    monbasis_predicted_values.(TLC_stages{stage})).^2);
monbasis_R_squared.(TLC_stages{stage}) = (error_sum_of_squares_Y.(
    TLC_stages{stage}) - monbasis_error_sum_of_squares_residuals.(TLC_stages
    {stage})) / error_sum_of_squares_Y.(TLC_stages{stage});
monbasis_adjusted_R_squared.(TLC_stages{stage}) = 1 - ((1 -
    monbasis_R_squared.(TLC_stages{stage})) * ((numel(technology.(TLC_stages
    {stage})) - 1) / (numel(technology.(TLC_stages{stage})) - numel(
    model_indicator_subset) - 1)));
```

```
monbasis_degrees_freedom_1 = monbasis_functional_regression.(TLC_stages{
    stage}).df - 1;
monbasis_degrees_freedom_2 = numel(technology.(TLC_stages{stage})) -
    monbasis_functional_regression.(TLC_stages{stage}).df;
monbasis_F_ratio.(TLC_stages{stage}) = ((error_sum_of_squares_Y.(TLC_stages
    {stage}) - monbasis_error_sum_of_squares_residuals.(TLC_stages{stage}))
    / monbasis_degrees_freedom_1) / (monbasis_error_sum_of_squares_residuals
    .(TLC_stages{stage}) / monbasis_degrees_freedom_2);

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Apply Functional Principal Components analysis (fPCA) to the functional
    covariates to build alternative functional model

% This section adapts the functional principal components analysis (fPCA)
% applied in section 9.4.5 of 'Functional Data Analysis with R and
% MATLAB.pdf' to evaluate an alternative patent indicator model
% formulation.

% Delete any pre-existing 'fPCA_table' to prevent error if only running
% this section of the script:
clear fPCA_table.(TLC_stages{stage});

% Set smoothing parameter, lambda, to apply to principal components
% analysis functional parameter objects:
if signal_alignment == 1
    fPCA_lambda.(TLC_stages{stage}) = 10^0;
else
    fPCA_lambda.(TLC_stages{stage}) = 10^0;
end

% Set number of principal components to keep for model building:
fPCA_num_kept_components.(TLC_stages{stage}) = 4;

% Preallocate empty cell arrays and table for storing principal components
% analysis functional parameter objects and results:
fPCA_patent_indicator_functional_parameter_object.(TLC_stages{stage}) =
    cell(numel(model_indicator_subset),1);
fPCA_patent_indicator.(TLC_stages{stage}) = cell(numel(
    model_indicator_subset),1);
fPCA_harmonics.(TLC_stages{stage}) = cell(numel(model_indicator_subset),1);
fPCA_variable_names.(TLC_stages{stage}) = cell(numel(model_indicator_subset
    )*fPCA_num_kept_components.(TLC_stages{stage}),1);
```

```
% Perform Functional Principal Components Analysis on each patent
% indicator included in the model:
for i = 1:numel(model_indicator_subset)
    % Select the current component of the selected model indicator subset:
    model_component = model_indicator_subset(i);

    % Build additional functional parameter object to use in the principal
    % components analysis alongside the functional data objects previously
    % created for the patent indicators included in the model:
    if signal_alignment == 1
        fPCA_patent_indicator_functional_parameter_object.(TLC_stages{stage
           }){i} = fdPar(patent_indicator_functional_basis_object.(
           TLC_stages{stage}){i},2,fPCA_lambda.(TLC_stages{stage}));
    else
        fPCA_patent_indicator_functional_parameter_object.(TLC_stages{stage
           }){i} = fdPar(patent_indicator_functional_basis_object.(
           TLC_stages{stage}){i},2,fPCA_lambda.(TLC_stages{stage}));
    end

    % Run functional principal components analysis with regularisation on
    % current patent indicator functional data object (see help on 'pca_fd'
    % for more details), keeping 4 of the principal components. For notes
    % on the impact of the number of retained components (or harmonics) on
    % the ability to capture important model features see section 7.4 of
    % 'Functional Data Analysis with R and MATLAB.pdf':
    fPCA_patent_indicator.(TLC_stages{stage}){i} = pca_fd(
       patent_indicator_FDO.(TLC_stages{stage}){i},fPCA_num_kept_components
       .(TLC_stages{stage}),
       fPCA_patent_indicator_functional_parameter_object.(TLC_stages{stage
       }){i});
    fPCA_harmonics.(TLC_stages{stage}){i} = fPCA_patent_indicator.(
       TLC_stages{stage}){i}.harmfd;

%     % Plot the principal components of the current patent indicator:
%     figure_name = ['Principal components for ',
   patent_indicator_column_names{model_component},' - ',TLC_stages{stage}];
%     figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
    scrsz(3), scrsz(4)]);
%     plot_pca_fd(fPCA_patent_indicator.(TLC_stages{stage}){i});
%     hold on
%
%     % Add title and X label to subplot:
%     title(figure_name);
%     xlabel('Normalised time (scaled)','FontSize',12)
%
```

```
%     % Set plots to be invisible now, but visible when opened later:
%     set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
%
%     % Save figure:
%     saveas(gcf,figure_name,'fig')
%     hold off

    % Plot the harmonics for the current patent indicator:
    figure_name = ['Harmonics for ',patent_indicator_column_names{
        model_component},' - ',TLC_stages{stage}];
    figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
        scrsz(3), scrsz(4)]);
    plot(fPCA_harmonics.(TLC_stages{stage}){i});
    hold on

    % Add title and X label to subplot:
    title(figure_name);
    xlabel('Normalised time (scaled)','FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off

    % Generate variable names for table of predictor variables:
    fPCA_component_labels.(TLC_stages{stage}) = {'A','B','C','D','E','F','G
        ','H','I','J'};
    for j = 1:fPCA_num_kept_components.(TLC_stages{stage})
        fPCA_variable_names.(TLC_stages{stage}){j+((i-1)*
            fPCA_num_kept_components.(TLC_stages{stage}))} = [
            fPCA_component_labels.(TLC_stages{stage}){i},num2str(j)];
    end

    % Add principal components analysis scores for the kept
    % components as values in a predictor variable table:
    fPCA_table.(TLC_stages{stage})(1:numel(technology.(TLC_stages{stage}))
        ,(1:fPCA_num_kept_components.(TLC_stages{stage}))+((i-1)*
        fPCA_num_kept_components.(TLC_stages{stage}))) = array2table(
        fPCA_patent_indicator.(TLC_stages{stage}){i}.harmscr);

    % Assemble string describing the components included for the
    % current patent indicator (for use in building factor description
    % for 'fitlm' - see below):
```

```
    fPCA_components.(TLC_stages{stage}){i} = strjoin(fPCA_variable_names.(
        TLC_stages{stage})((1:fPCA_num_kept_components.(TLC_stages{stage}))
        +((i-1)*fPCA_num_kept_components.(TLC_stages{stage}))),' + ');
end

% Assign headings to table variables:
fPCA_table.(TLC_stages{stage}).Properties.VariableNames =
    fPCA_variable_names.(TLC_stages{stage});

% Append response variable Y as the last column in the table (taken as
% default in 'fitlm' to be the response variable):
fPCA_table.(TLC_stages{stage}).Responses = technology_data_filtered.
    known_cluster_id.(TLC_stages{stage});

% Construct string describing the factors to include in the linear
% regression model using 'Wilkinson Notation' (see Matlab reference page
% for fitlm for explanation of this notation):
fPCA_factor_equation.(TLC_stages{stage}) = ['Responses ~ (',strjoin(
    fPCA_components.(TLC_stages{stage}),') + ('),')'];

% Fit linear regression model based on the principal component scores
% stored in the predictor table (equivalent of 'pcamodel' on page 143,
% section 9.4.5 of 'Functional Data Analysis with R and MATLAB.pdf'):
fPCA_model.(TLC_stages{stage}) = fitlm(fPCA_table.(TLC_stages{stage}),
    fPCA_factor_equation.(TLC_stages{stage}));

% Extract functional principal component analysis coefficients for building
% linear regression model (equivalent of 'pcacoefs' on page 143, section
% 9.4.5 of 'Functional Data Analysis with R and MATLAB.pdf'):
fPCA_coefficients.(TLC_stages{stage}) = fPCA_model.(TLC_stages{stage}).
    Coefficients;

% Determine the variance of the coefficients from the fPCA coefficients
% (equivalent of 'coefvar' on page 143, section 9.4.5 of 'Functional Data
% Analysis with R and MATLAB.pdf'):
fPCA_coefficient_variance.(TLC_stages{stage}) = fPCA_coefficients.(
    TLC_stages{stage}){:,2}.^2;

% Create the corresponding functional data objects for the fPCA regression
% functions:
for i = 1:numel(model_indicator_subset)
    % Select the current component of the selected model indicator subset:
    model_component = model_indicator_subset(i);

    % Combine the fPCA coefficients with the fPCA harmonic functions for
    % the current patent indicator (equivalent of 'betafd' on page 143,
```

```
% section 9.4.5 of 'Functional Data Analysis with R and MATLAB.pdf'):
for j = 1:(fPCA_num_kept_components.(TLC_stages{stage}))
    fPCA_estimated_beta_functional_data_object_harmonics.(TLC_stages{
       stage}){i,j} = times(fPCA_coefficients.(TLC_stages{stage}){j
       +1+((i-1)*fPCA_num_kept_components.(TLC_stages{stage})),1},
       fPCA_harmonics.(TLC_stages{stage}){i}(j));
    if j == 1
        fPCA_estimated_beta_functional_data_object.(TLC_stages{stage}){
           i} = fPCA_estimated_beta_functional_data_object_harmonics.(
           TLC_stages{stage}){i,j};
    else
        fPCA_estimated_beta_functional_data_object.(TLC_stages{stage}){
           i} = fPCA_estimated_beta_functional_data_object.(TLC_stages{
           stage}){i} +
           fPCA_estimated_beta_functional_data_object_harmonics.(
           TLC_stages{stage}){i,j};
    end
end

% Combine the fPCA coefficient variances with the square of the fPCA
% harmonic functions for the current patent indicator (equivalent of
% 'betavar' on page 143, section 9.4.5 of 'Functional Data Analysis
% with R and MATLAB.pdf'):
for j = 1:(fPCA_num_kept_components.(TLC_stages{stage}))
    fPCA_beta_variance_harmonics.(TLC_stages{stage}){i,j} = times(
       fPCA_coefficient_variance.(TLC_stages{stage})(j+1+((i-1)*
       fPCA_num_kept_components.(TLC_stages{stage}))),power(
       fPCA_harmonics.(TLC_stages{stage}){i}(j),2));
    if j == 1
        fPCA_beta_variance.(TLC_stages{stage}){i} =
           fPCA_beta_variance_harmonics.(TLC_stages{stage}){i,j};
    else
        fPCA_beta_variance.(TLC_stages{stage}){i} = fPCA_beta_variance
           .(TLC_stages{stage}){i} + fPCA_beta_variance_harmonics.(
           TLC_stages{stage}){i,j};
    end
end

% Plot the current fPCA regression coefficient along with 95%
   confidence
% bounds:
figure_name = ['Estimated fPCA regression coefficient for predicting
   technology cluster from ',patent_indicator_column_names{
   model_component},' - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1,
   scrsz(3), scrsz(4)]);
```

```
    hold on
    plot(fPCA_estimated_beta_functional_data_object.(TLC_stages{stage}){i})
        ;
    line(fPCA_estimated_beta_functional_data_object.(TLC_stages{stage}){i}+
        times(sqrt(fPCA_beta_variance.(TLC_stages{stage}){i}),2));
    line(fPCA_estimated_beta_functional_data_object.(TLC_stages{stage}){i}-
        times(sqrt(fPCA_beta_variance.(TLC_stages{stage}){i}),2));

    % Resize y-axis to fit the confidence bounds curves:
    ylim('auto');

    % Add title, X, and Y labels to subplot:
    title(figure_name);
    xlabel('Normalised time (scaled)','FontSize',12)
    ylabel(['Beta for ',patent_indicator_column_names{model_component}],'
        FontSize',12)

    % Set plots to be invisible now, but visible when opened later:
    set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

    % Save figure:
    saveas(gcf,figure_name,'fig')
    hold off
end

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Set figures generated to be visible again by default:
set(0,'DefaultFigureVisible','on')

%% Apply permutation testing to the regression functions estimated by the
    high-dimensional functional regression model in order to evaluate the F-
    statistic

% NB: THIS SECTION OF THE SCRIPT TAKES A LONG TIME TO RUN, SO ONLY RUN IT
% WHEN NEEDED!

% Generate figure for visual displaying the null distribution versus the
% qth quantile and observed F-statistic:
figure_name = ['Permutation F-Test and null distribution for the high-
    dimensional functional regression model - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
```

```
hold on

% Count the proportion of permutation F values that are larger than the F
% statistic for the high-dimensional functional regression model (see help
% on 'Fperm_fd' for details, along with section 9.5 of 'Functional Data
% Analysis with R and MATLAB.pdf'):
F_permutation_test.(TLC_stages{stage}) = Fperm_fd(technology_data_filtered.
    known_cluster_id.(TLC_stages{stage}),covariates.(TLC_stages{stage}),
    beta_basis_systems.(TLC_stages{stage}),[],1000,[],0.95,1);

% Add title and Y label to plot:
title(figure_name);
ylabel('Frequency of F values','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Apply permutation testing to the regression functions estimated by the
    low-dimensional functional regression model in order to evaluate the F-
    statistic

% NB: THIS SECTION OF THE SCRIPT TAKES A LONG TIME TO RUN, SO ONLY RUN IT
% WHEN NEEDED!

% Generate figure for visual displaying the null distribution versus the
% qth quantile and observed F-statistic:
figure_name = ['Permutation F-Test and null distribution for the low-
    dimensional functional regression model - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on

% Count the proportion of permutation F values that are larger than the F
% statistic for the low-dimensional functional regression model (see help
% on 'Fperm_fd' for details, along with section 9.5 of 'Functional Data
% Analysis with R and MATLAB.pdf'):
```

```
low_dimensional_F_permutation_test.(TLC_stages{stage}) = Fperm_fd(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),low_dimensional_beta_basis_systems.(TLC_stages{
    stage}),[],1000,[],0.95,1);

% Add title and Y label to plot:
title(figure_name);
ylabel('Frequency of F values','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Apply permutation testing to the regression functions estimated by the
    constant basis system functional regression model in order to evaluate
    the F-statistic

% NB: THIS SECTION OF THE SCRIPT TAKES A LONG TIME TO RUN, SO ONLY RUN IT
% WHEN NEEDED!

% Generate figure for visual displaying the null distribution versus the
% qth quantile and observed F-statistic:
figure_name = ['Permutation F-Test and null distribution for the constant
    basis system functional regression model - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on

% Count the proportion of permutation F values that are larger than the F
% statistic for the constant basis system functional regression model (see
% help on 'Fperm_fd' for details, along with section 9.5 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
conbasis_F_permutation_test.(TLC_stages{stage}) = Fperm_fd(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),conbasis_beta_basis_systems.(TLC_stages{stage})
    ,[],1000,[],0.95,1);

% Add title and Y label to plot:
```

```
title(figure_name);
ylabel('Frequency of F values','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')

% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()

%% Apply permutation testing to the regression functions estimated by the
    monomial basis system functional regression model in order to evaluate
    the F-statistic

% NB: THIS SECTION OF THE SCRIPT TAKES A LONG TIME TO RUN, SO ONLY RUN IT
% WHEN NEEDED!

% Generate figure for visual displaying the null distribution versus the
% qth quantile and observed F-statistic:
figure_name = ['Permutation F-Test and null distribution for the monomial
    basis system functional regression model - ',TLC_stages{stage}];
figure('Name',figure_name,'NumberTitle','off','OuterPosition', [1, 1, scrsz
    (3), scrsz(4)]);
hold on

% Count the proportion of permutation F values that are larger than the F
% statistic for the monomial basis system functional regression model (see
% help on 'Fperm_fd' for details, along with section 9.5 of 'Functional
% Data Analysis with R and MATLAB.pdf'):
monbasis_F_permutation_test.(TLC_stages{stage}) = Fperm_fd(
    technology_data_filtered.known_cluster_id.(TLC_stages{stage}),covariates
    .(TLC_stages{stage}),monbasis_beta_basis_systems.(TLC_stages{stage})
    ,[],1000,[],0.95,1);

% Add title and Y label to plot:
title(figure_name);
ylabel('Frequency of F values','FontSize',12)

% Set plots to be invisible now, but visible when opened later:
set(gcf,'Visible','off','CreateFcn','set(gcf,''Visible'',''on'')')
```

```
% Save figure:
saveas(gcf,figure_name,'fig')
hold off

%% Save all variables to a MAT file:
save('functional_data_analysis.mat');

toc()
```

Appendix E - Historical technology adoption data and sources

IEA 4E notes on data from UK mapping and benchmarking report (Table E1):

1. Data presented is from two separate sources:
   a) 1999-2010: Projections derived from annual sales values based on modelling (although with supporting verification). Data supplier views the sales values provided as relatively robust (with some caveats) for all domestic (household) sector lamps used in the residential sector only
   b) 2011-2013: Based on annual sales data by lamp type scaled up (linearly) to account for estimated market coverage of approximately 80-90% for all lamps and 60-70% for LEDs
2. Annual market average efficacies calculated on a sales weighted basis using estimated average global efficacies for each lamp type and associated wattage range for 230V lamps.
3. The large volume of CFL sales in 2008-10, and resultant spike in average market efficacy, is likely to be caused by a UK policy (the Carbon Emissions Reduction Target) as a result of which utilities distributed large numbers of CFLs in those years.

Notes on Table E3: * = based on ICCT EU Pocketbook market share data for combined Battery Electric Vehicle and Plug-in Hybrid Electric Vehicle sales

Year	Annual UK sales of lights by type (millions)						UK market share for lights by type [%]				
	LEDs	LFTs	CFLs	Halogens	Incandescents	All lights	LEDs	LFTs	CFLs	Halogens	Incandescents
1999	0.00	2.20	8.30	18.00	172.70	201.20	0.00	1.09	4.13	8.95	85.83
2000	0.00	2.10	8.80	18.30	173.30	202.50	0.00	1.04	4.35	9.04	85.58
2001	0.00	2.10	9.30	19.40	167.30	198.10	0.00	1.06	4.69	9.79	84.45
2002	0.00	2.10	9.70	23.50	162.50	197.80	0.00	1.06	4.90	11.88	82.15
2003	0.00	2.00	10.20	28.60	159.70	200.50	0.00	1.00	5.09	14.26	79.65
2004	0.00	2.00	10.70	32.00	154.80	199.50	0.00	1.00	5.36	16.04	77.59
2005	0.00	1.90	11.30	34.80	150.70	198.70	0.00	0.96	5.69	17.51	75.84
2006	0.00	1.80	11.90	38.50	147.00	199.20	0.00	0.90	5.97	19.33	73.80
2007	0.00	1.60	12.40	42.50	142.90	199.40	0.00	0.80	6.22	21.31	71.66
2008	0.00	1.50	36.50	32.90	128.50	199.40	0.00	0.75	18.30	16.50	64.44
2009	0.00	1.30	72.60	36.20	88.60	198.70	0.00	0.65	36.54	18.22	44.59
2010	0.00	1.10	96.00	57.80	38.30	193.20	0.00	0.57	49.69	29.92	19.82
2011	1.40	1.20	35.90	60.10	96.40	195.00	0.72	0.62	18.41	30.82	49.44
2012	2.20	1.10	18.30	76.50	60.10	158.20	1.39	0.70	11.57	48.36	37.99
2013	4.60	1.20	17.40	93.60	23.30	140.10	3.28	0.86	12.42	66.81	16.63

Table E1: UK market share for domestic lights by type (Source: [International Energy Agency 4E, 2014])

Year	Belgium	Bulgaria	Czech Republic	Denmark	Germany (until 1990 former territory of the FRG)	Estonia	Ireland	Greece	Spain	France	Croatia	Italy	Cyprus	Latvia	Lithuania	Luxembourg	Hungary	Malta
1970	295,701	:	:	108,634	2,107,123	:	:	32,354	572,346	1,296,240	:	1,363,594	:	:	:	11,633	:	:
1975	357,897	:	:	115,733	2,106,048	:	:	60,135	573,247	1,482,310	:	1,050,947	:	:	:	17,356	:	:
1979	423,668	:	:	127,114	2,623,400	:	:	87,169	620,652	1,976,391	:	1,397,039	:	:	:	22,796	:	:
1980	401,611	:	:	73,961	2,426,187	:	:	41,841	574,149	1,873,202	:	1,530,488	:	:	:	22,440	:	:
1981	352,613	:	:	71,778	2,330,335	:	:	54,879	505,716	1,834,646	:	1,808,476	:	:	:	23,008	:	:
1982	346,303	:	:	85,512	2,155,537	:	:	91,929	535,733	2,056,490	:	1,851,174	:	:	:	25,796	:	:
1983	341,243	:	:	116,346	2,426,774	:	:	75,222	550,436	2,017,617	:	1,451,512	:	:	:	26,482	:	:
1984	354,051	:	:	134,478	2,393,939	:	:	85,945	522,229	1,757,673	:	1,572,402	:	:	:	28,597	:	:
1985	361,948	:	:	157,632	2,379,261	:	:	109,435	575,052	1,766,328	:	1,653,217	:	:	:	29,235	:	:
1986	397,156	:	:	169,492	2,829,438	:	:	96,181	689,051	1,911,521	:	1,854,618	:	:	:	32,960	:	:
1987	408,879	:	:	124,324	2,915,654	:	:	74,180	928,264	2,105,180	:	2,037,031	:	:	:	32,660	:	:
1988	430,520	:	:	88,770	2,807,939	:	:	76,043	1,069,220	2,217,149	:	2,167,362	:	:	:	33,847	:	:
1989	443,963	:	:	78,453	2,831,740	:	:	102,314	1,149,373	2,274,307	:	2,391,966	:	:	:	34,382	:	:
1990	478,219	46,433	:	80,837	3,040,783	:	83,420	132,487	1,007,014	2,309,130	66,214	2,395,909	19,532	:	:	38,648	143,073	8,218
1991	46,766	31,093	:	83,828	:	:	68,533	176,862	914,061	2,031,274	85,813	2,217,257	17,681	:	:	44,055	:	:
1992	485,697	44,186	:	84,170	3,929,558	36,284	67,861	206,652	1,008,454	2,105,700	31,928	2,341,402	18,178	:	:	37,133	45,122	:
1993	392,530	83,713	:	82,205	3,194,204	53,168	60,792	155,646	775,461	1,721,222	59,337	1,645,162	12,968	:	:	30,679	63,058	:
1994	403,981	76,529	:	139,251	3,209,224	51,217	77,773	118,088	938,971	1,972,919	58,499	1,610,561	13,358	:	:	30,124	45,833	:
1995	370,165	56,702	:	135,058	3,314,061	44,471	82,730	133,757	870,497	1,930,504	67,576	1,766,101	17,938	49,322	154,850	:	55,970	10,102
1996	408,285	69,500	:	142,175	3,496,320	35,621	109,333	141,589	968,363	2,132,091	73,584	1,843,366	20,402	52,112	122,142	:	62,660	10,624
1997	:	28,166	:	152,869	3,528,179	9,448	125,818	166,778	1,091,190	1,713,030	109,144	2,389,892	20,290	71,513	173,057	:	70,827	9,226
1998	463,724	70,797	:	162,708	3,735,987	8,400	138,538	183,657	1,282,970	1,943,553	85,893	2,437,718	24,856	57,363	147,105	36,353	101,328	10,750
1999	504,203	103,459	:	144,259	3,802,176	6,864	170,322	268,716	1,502,531	2,148,423	89,846	2,312,309	20,133	45,861	142,069	40,989	126,085	13,341
2000	531,640	98,185	:	113,631	3,378,343	10,240	225,269	302,620	1,467,160	2,133,884	92,759	2,359,674	19,056	35,745	115,808	42,304	130,323	13,055
2001	499,779	117,333	:	96,114	3,341,718	12,822	160,908	289,943	1,498,899	2,254,732	108,484	2,379,980	24,533	37,850	71,328	43,164	137,771	10,295
2002	472,830	121,512	:	111,598	3,252,898	14,701	150,485	277,567	1,408,426	2,145,071	94,989	2,235,948	28,101	40,335	93,305	43,677	160,238	10,267
2003	463,173	143,480	144,849	:	3,236,938	15,824	142,992	272,515	:	2,009,246	104,399	:	29,961	50,290	118,263	43,765	190,107	:
2004	489,346	150,803	123,579	:	3,266,826	16,514	149,635	:	:	2,013,709	99,863	:	43,842	57,474	134,612	48,273	188,488	:
2005	484,915	168,102	125,166	:	3,342,122	:	:	:	:	:	101,916	:	38,676	69,704	173,644	48,517	:	:
2006	530,941	182,095	120,370	131,605	3,467,961	25,372	:	:	1,660,627	2,000,549	114,680	:	37,192	97,399	185,271	50,837	151,670	:
2007	529,606	348,887	129,443	252,183	3,148,163	30,916	180,754	:	1,633,806	2,064,543	108,015	2,514,905	50,908	107,003	220,236	51,332	136,032	:
2008	540,542	351,433	141,954	184,323	3,090,040	24,590	:	:	1,188,485	2,050,283	96,712	2,193,822	51,410	54,759	191,768	52,359	176,678	9,598
2009	479,920	201,304	160,614	:	3,807,175	9,948	:	:	971,177	2,269,011	53,569	2,176,940	37,494	17,288	136,803	47,264	:	15,816
2010	551,661	186,092	168,372	:	2,916,260	10,294	:	:	1,000,010	2,209,454	46,437	1,971,830	32,680	26,656	161,266	:	61,324	13,605
2011	577,382	191,430	172,787	:	3,173,634	17,058	104,022	:	817,688	2,160,920	48,883	1,764,592	27,929	43,468	132,117	:	76,528	15,875
2012	:	196,614	174,311	:	3,082,504	19,422	77,506	:	710,638	1,857,013	40,825	1,403,043	20,556	50,135	:	:	106,671	13,037
2013	:	:	:	:	2,952,431	19,690	74,960	:	:	:	46,563	:	14,771	55,808	:	:	:	:

Year	Netherlands	Austria	Poland	Portugal	Romania	Slovenia	Slovakia	Finland	Sweden	United Kingdom	Iceland	Liechtenstein	Norway	Switzerland	Former Yugoslav Republic of Macedonia, the	Turkey	Total
1970	432,231	:	:	83,800	:	:	:	:	:	1,116,196	:	:	:	:	:	:	7,419,852
1975	450,220	:	:	90,167	:	:	:	:	:	1,197,206	:	:	:	:	:	:	7,501,266
1979	575,059	:	:	77,281	:	:	:	:	:	1,764,437	:	:	:	:	:	:	9,695,006
1980	450,974	:	:	97,034	:	:	:	:	:	1,566,459	:	:	:	:	:	:	9,058,346
1981	389,312	:	:	123,149	:	:	:	:	:	1,539,586	:	:	:	:	:	:	9,033,498
1982	406,774	:	:	129,631	:	:	:	:	:	1,676,982	:	:	:	:	:	:	9,361,861
1983	459,131	:	:	113,632	:	:	:	:	:	1,938,169	:	:	:	:	:	:	9,516,564
1984	461,391	:	:	103,264	:	:	:	:	:	1,893,313	:	:	:	:	:	:	9,307,282
1985	495,685	:	:	104,423	:	:	:	:	:	1,983,096	:	:	:	:	:	:	9,615,312
1986	560,512	:	:	114,400	:	:	:	:	:	2,024,992	:	:	:	:	:	:	10,680,321
1987	555,743	:	:	938,889	:	:	:	:	:	2,166,201	:	:	:	:	:	:	12,287,005
1988	482,617	:	:	208,629	:	:	:	:	:	2,382,480	:	:	70,611	319,408	:	:	12,354,595
1989	495,653	276,065	:	192,772	:	:	:	177,610	314,126	2,480,048	:	:	56,944	338,969	:	:	13,638,685
1990	502,671	288,636	358,055	212,348	:	:	:	139,742	235,192	2,075,982	:	:	63,668	322,974	13,809	218,059	14,281,053
1991	490,407	303,723	734,885	231,176	:	:	:	92,979	191,755	1,665,664	:	:	55,111	310,193	13,069	:	9,806,185
1992	492,130	320,094	471,026	280,035	:	31,191	:	68,891	157,295	1,663,846	:	:	61,648	286,289	4,802	317,044	14,596,616
1993	391,934	285,162	477,353	248,462	:	59,878	41,694	56,003	127,738	1,845,714	5,662	:	63,988	256,917	8,361	441,534	12,640,545
1994	433,913	273,663	486,600	243,254	:	47,217	:	67,434	159,578	1,982,929	5,570	:	91,336	265,892	10,152	244,289	13,058,155
1995	:	279,610	450,769	228,812	:	61,700	:	80,145	175,061	1,938,100	6,931	2	97,880	267,975	14,268	200,658	12,861,715
1996	:	307,671	627,349	268,542	:	59,358	107,576	96,163	200,154	2,105,914	9,515	2	146,835	272,214	13,270	219,230	14,121,960
1997	478,318	275,001	722,245	287,730	125,142	64,357	85,551	104,963	258,944	2,250,870	11,734	2	154,654	270,625	8,911	299,108	15,057,582
1998	543,110	295,865	557,783	323,981	105,986	71,022	76,007	126,386	286,671	2,362,589	15,064	2	141,090	295,165	8,676	271,843	16,372,940
1999	611,776	314,182	599,250	351,575	90,047	81,869	58,152	137,017	327,710	2,414,660	17,007	2	123,843	314,691	9,840	:	16,893,207
2000	597,623	309,427	519,407	340,397	:	64,846	54,352	135,243	342,965	2,432,149	14,769	2	126,978	314,482	13,763	354,013	16,690,112
2001	530,287	293,528	450,095	302,763	:	55,432	66,759	109,911	280,280	2,663,288	7,669	2	:	314,580	4,755	117,196	16,282,198
2002	510,744	279,493	421,167	267,374	:	52,310	67,298	117,486	281,446	2,756,342	7,375	2	:	293,034	32,641	170,191	15,918,851
2003	488,977	300,121	274,392	:	:	55,314	71,954	148,020	293,035	2,720,096	10,833	1,770	:	269,711	:	176,217	11,776,242
2004	483,885	311,292	833,021	:	149,290	58,945	71,954	143,160	297,405	2,668,449	13,927	1,790	145,538	267,476	:	432,728	12,661,824
2005	465,196	:	979,082	:	:	60,531	:	:	297,050	:	22,141	:	:	260,682	15,894	406,807	7,060,145
2006	483,999	308,594	923,783	:	312,515	59,885	:	146,201	300,502	:	:	1,890	142,572	269,700	12,450	396,542	12,115,202
2007	505,643	298,182	1,128,684	:	436,349	67,791	146,292	126,022	321,705	:	:	1,990	162,970	284,000	16,914	353,495	15,356,769
2008	499,921	293,697	1,280,633	:	586,476	71,037	151,814	140,216	257,806	2,112,000	:	2,005	138,241	288,000	17,914	353,168	16,591,684
2009	:	319,403	864,295	181,132	328,880	57,391	148,370	90,923	212,695	1,968,000	:	1,620	125,903	266,500	13,113	357,986	15,320,534
2010	:	328,563	873,098	248,813	309,952	60,777	126,663	112,418	:	1,996,324	:	1,782	159,374	296,600	49,291	485,619	14,405,215
2011	:	356,145	928,457	177,183	176,555	59,813	130,772	126,651	326,301	1,907,411	:	:	168,552	328,000	40,090	602,248	14,652,491
2012	:	336,010	908,906	110,002	242,025	49,700	130,818	111,664	:	:	:	:	171,828	334,000	32,870	565,791	10,745,889
2013	:	:	987,809	:	:	51,968	:	103,450	:	:	:	1,920	176,019	:	:	654,905	5,140,294

Table E2: New registrations of passenger cars in the EU by type of motor energy and engine size, including alternative motor energy vehicles (Source: [Eurostat, 2017] [road_eqr_carm])

Year	Country														
	Belgium	Bulgaria	Germany (until 1990 former territory of the FRG)	Estonia	Ireland	Greece	Spain	France	Croatia	Italy	Cyprus	Latvia	Lithuania	Luxembourg	Hungary
1987	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
1989	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
1990	:	:	:	:	:	:	:	:	:	:	0	:	:	:	:
1991	:	:	:	:	:	:	:	:	:	:	0	:	:	:	:
1992	:	:	460	:	:	:	:	:	:	:	0	:	:	:	0
1993	:	:	339	:	:	:	:	:	:	:	0	:	:	:	11
1994	:	:	213	:	:	:	:	32	:	:	0	:	:	:	13
1995	:	:	208	:	:	:	:	132	:	:	0	0	:	:	11
1996	:	:	272	:	:	:	:	490	:	:	0	0	:	:	0
1997	:	:	263	:	:	5	:	299	:	:	0	0	:	:	0
1998	:	:	210	:	:	1	:	505	:	:	:	0	:	:	:
1999	:	:	121	:	0	15	:	529	:	:	:	0	:	:	1
2000	:	:	109	:	0	15	:	241	:	:	:	0	:	:	0
2001	:	:	47	:	0	2	:	407	:	:	:	0	:	:	0
2002	:	:	19	:	0	0	:	310	:	:	:	0	:	:	0
2003	:	:	28	:	0	0	:	113	:	:	:	0	:	:	:
2004	265	:	61	0	0	:	:	460	4	:	:	0	0	:	0
2005	0	:	47	:	:	:	:	:	3	:	:	0	0	:	:
2006	0	:	19	0	:	:	:	14	:	:	:	0	0	0	:
2007	0	:	8	0	:	:	:	6	41	:	2	0	0	0	:
2008	0	:	36	1	:	:	:	4	48	:	379	0	0	1	:
2009	0	:	162	0	:	:	:	12	29	:	206	0	0	0	:
2010	47	:	541	1	:	:	:	:	23	:	195	0	0	:	13
2011	264	:	2,154	56	68	:	:	:	45	:	267	0	2	:	12
2012	:	:	2,956	512	137	:	:	5,661	63	:	177	10	:	:	17
2013	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
2014	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
2015	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:

Year	Country													Total	Market share [%]
	Malta	Netherlands	Austria	Romania	Slovenia	Finland	Sweden	United Kingdom	Iceland	Liechtenstein	Norway	Switzerland	Turkey		
1987	:	:	:	:	:	:	:	:	:	:	:	:	:	0	0.00
1989	:	:	:	:	:	:	:	:	:	:	:	101	:	101	0.00
1990	:	:	:	:	:	:	:	:	:	:	:	214	:	214	0.00
1991	:	:	:	:	:	2	:	:	:	:	:	259	:	261	0.00
1992	:	:	:	:	:	1	:	:	:	:	:	124	:	585	0.01
1993	:	:	:	:	1	:	:	:	:	:	:	84	:	435	0.00
1994	:	:	:	:	0	:	:	:	:	:	:	:	:	258	0.00
1995	:	:	13	:	0	:	:	:	0	:	:	61	:	425	0.00
1996	:	:	20	:	0	2	:	:	0	:	:	90	:	874	0.01
1997	:	:	18	:	0	0	:	27	:	:	:	61	:	673	0.00
1998	10	:	12	:	0	0	:	41	4	:	:	57	:	840	0.01
1999	:	:	3	:	0	3	15	:	:	:	:	71	:	758	0.00
2000	1	:	3	:	0	:	15	55	2	:	:	64	:	505	0.00
2001	3	:	5	:	0	:	2	77	:	0	:	16	:	559	0.00
2002	5	:	1	:	0	:	2	62	:	:	:	75	:	474	0.00
2003	:	:	:	:	:	:	1	39	:	0	:	18	:	199	0.00
2004	:	:	1	:	:	0	0	90	0	0	127	20	:	1,028	0.01
2005	:	:	:	:	:	:	1	:	:	:	:	13	:	64	0.00
2006	:	:	0	:	:	0	0	:	:	0	210	0	:	243	0.00
2007	:	:	0	:	:	0	2	:	:	0	100	0	:	159	0.00
2008	4	:	2	:	:	5	1	220	:	0	275	0	:	976	0.01
2009	2	:	39	1	:	1	28	181	:	0	180	0	:	841	0.01
2010	3	:	112	187	:	15	:	255	:	0	406	200	:	1,998	0.01
2011	2	:	631	270	:	30	185	1,204	:	:	2,029	500	:	7,719	0.05
2012	8	:	427	405	:	51	:	:	:	:	4,259	900	186	15,769	0.11
2013	:	:	:	:	:	:	:	:	:	:	:	:	:	:	0.42*
2014	:	:	:	:	:	:	:	:	:	:	:	:	:	:	0.50*
2015	:	:	:	:	:	:	:	:	:	:	:	:	:	:	1.00*

Table E3: New registrations of passenger cars, motor coaches, buses and trolley buses in the EU by type of vehicle and alternative motor energy (Sources: [Eurostat, 2017] [road_eqr_carbua] & [The International Council on Clean Transportation, 2016])

Year	U.S. market share by type of personal printer [%]				Comment	Sources
	Impact / Dot - matrix	Thermal	Inkjet	Laser		
1983	72.00	:	:	:		Compute! (Atari Magazine) - Issue 49, June 1984, Page 18
1984	:	:	:	2.50	Average based on the 2 or 3% of new printers in 1984 quoted as being laser printers in 'PC Magazine'	PC Magazine - June 12th 1990, Page 114
1985	:	12.00	:	:	Predicted value (from historical source)	Compute! (Atari Magazine) - Issue 49, June 1984, Page 18
1988	73.00	:	:	:	Based on survey of 'PC Magazine' readers in 1988	PC Magazine - October 31st 1988, Page 94
1989	72.22	4.17	8.33	15.28		PC Magazine - November 26th 1991, Page 113
1990	65.43	3.70	8.64	22.22		PC Magazine - November 26th 1991, Page 113
1991	61.45	2.41	12.05	24.10		PC Magazine - November 26th 1991, Page 113
1992	55.92	1.13	16.95	26.00		PC Magazine - November 23rd 1993, Page 110
1993	41.83	0.94	29.79	27.44		PC Magazine - November 22nd 1994, Page 114
1994	29.73	0.76	40.03	29.48	Predicted values (from historical source)	PC Magazine - November 22nd 1994, Page 114
1995	20.09	0.77	57.18	21.96	Predicted values (from historical source)	PC Magazine - November 7th 1995, Page 104
1996	9.32	0.50	76.59	13.59	Predicted or estimated values (from historical source)	PC Magazine - November 7th 1995, Page 104 & November 5th 1996, Page 102
1997	8.38	0.59	75.84	15.20	Predicted values (from historical source)	PC Magazine - November 7th 1995, Page 104
1998	2.96	0.30	64.22	15.95	Predicted or estimated values (from historical source)	PC Magazine - November 7th 1995, Page 104 & November 2nd 1999, Pages 178 & 179
1999	4.02	0.55	82.51	12.92	Predicted values (from historical source)	PC Magazine - November 7th 1995, Page 104
2000 (Q3)	:	:	77.00	:		HUBBARD, 2001
2000 (Q4)	:	:	81.00	12.00		HUBBARD, 2001
2003	:	:	76.38	9.39	Predicted values (from historical source)	PC Magazine - November 2nd 1999, Pages 178 & 179
2009 (Q4)	:	:	70.00	:		International Data Corporation
2012	:	:	59.81	40.19	Approximate market share values based on quoted number of installed printer types	IT Candor
2013	:	:	58.89	41.11	Approximate market share values based on quoted number of installed printer types	IT Candor
2014	:	:	57.95	42.05	Approximate market share values based on quoted number of installed printer types	IT Candor
2015	:	:	58.00	43.18	Approximate market share values based on quoted number of installed printer types	IT Candor, Forbes 2015

Table E4: US market share for personal printers by type

Year	Share of World Electricity Output [%]						
	Nuclear	Hydro	Geothermal (direct use in TJ-net)	Solar photovoltaics	Solar thermal (direct use in TJ-net)	Tide, wave and ocean	Wind
1971	2.10880	23.07097	0.08579	0.00000	0.00000	0.00951	0.00000
1972	2.67021	22.39841	0.09485	0.00000	0.00000	0.00965	0.00000
1973	3.30703	21.09021	0.10790	0.00000	0.00000	0.00910	0.00000
1974	4.32992	22.74908	0.11059	0.00000	0.00000	0.00948	0.00000
1975	5.87580	22.28872	0.12267	0.00000	0.00000	0.00792	0.00000
1976	6.29821	20.70150	0.12764	0.00000	0.00000	0.00626	0.00000
1977	7.33728	20.40706	0.12155	0.00000	0.00000	0.00622	0.00000
1978	8.12176	20.95966	0.11253	0.00000	0.00000	0.00610	0.00004
1979	8.06941	21.15898	0.13404	0.00000	0.00000	0.00617	0.00007
1980	8.59570	20.87651	0.16440	0.00000	0.00000	0.00596	0.00013
1981	9.94334	20.95343	0.18139	0.00000	0.00000	0.00663	0.00013
1982	10.63292	21.22118	0.18792	0.00000	0.00000	0.00700	0.00022
1983	11.60181	21.30925	0.20232	0.00003	0.00000	0.00676	0.00034
1984	13.32249	20.85918	0.21887	0.00014	0.00000	0.00648	0.00040
1985	15.19253	20.38161	0.23338	0.00018	0.00000	0.00637	0.00058
1986	15.82806	20.12292	0.25425	0.00019	0.00001	0.00612	0.00134
1987	16.38943	19.41352	0.26415	0.00013	0.00002	0.00570	0.00183
1988	17.08727	19.22839	0.25624	0.00009	0.00001	0.00531	0.00304
1989	16.69611	18.24819	0.29169	0.00010	0.00422	0.00503	0.02343
1990	16.89644	18.40065	0.30575	0.00018	0.00557	0.00450	0.03257
1991	17.26977	18.60734	0.30663	0.00022	0.00639	0.00456	0.03442
1992	17.26618	18.42848	0.31942	0.00049	0.00606	0.00452	0.03769
1993	17.39032	19.03670	0.31945	0.00067	0.00712	0.00424	0.04454
1994	17.37557	18.75144	0.31810	0.00081	0.00639	0.00419	0.05665
1995	17.46503	19.07023	0.29879	0.00100	0.00617	0.00410	0.05959
1996	17.54212	18.76390	0.30615	0.00118	0.00655	0.00385	0.06861
1997	17.00681	18.59294	0.30123	0.00154	0.00635	0.00390	0.08589
1998	16.93460	18.21989	0.31408	0.00238	0.00614	0.00389	0.11136
1999	17.04445	17.75611	0.32767	0.00418	0.00355	0.00373	0.14532
2000	16.65826	17.36153	0.33431	0.00663	0.00338	0.00351	0.20158
2001	16.83187	16.85684	0.32911	0.00828	0.00361	0.00334	0.24514
2002	16.33989	16.65085	0.32114	0.01021	0.00349	0.00327	0.32430
2003	15.61299	16.14966	0.32045	0.01257	0.00325	0.00314	0.38030
2004	15.51372	16.41157	0.32015	0.01594	0.00333	0.00288	0.47814
2005	15.03621	16.39761	0.31661	0.02194	0.00324	0.00280	0.56431
2006	14.60510	16.36960	0.31189	0.02951	0.00288	0.00256	0.69594
2007	13.63910	15.88560	0.31245	0.03786	0.00344	0.00248	0.85670
2008	13.45691	16.20139	0.31963	0.05902	0.00442	0.00240	1.08826
2009	13.32681	16.51645	0.33137	0.09921	0.00457	0.00240	1.37121
2010	12.77130	16.36142	0.31565	0.14996	0.00763	0.00238	1.58156
2011	11.59233	16.15935	0.31072	0.28396	0.01285	0.00229	1.95480
2012	10.80154	16.50657	0.30829	0.43359	0.02092	0.00218	2.29871
2013	10.57029	16.55526	0.30542	0.59882	0.02529	0.00395	2.75247
2014	10.60657	16.66088	0.32371	0.79357	0.03552	0.00418	3.00080

Table E5: Global market share for low-carbon electricity generation sources (Sources: [International Energy Agency, 2016, UK Data Service, 2017])

Year	Global market share by technology [%]					
	Mobile-cellular telephone subscriptions (per 100 people) [ITU]	Mobile-cellular telephone subscriptions (per 100 people) [World Bank]	Individuals using the Internet [ITU]	Fixed-telephone subscriptions [ITU]	Active mobile-broadband subscriptions [ITU]	Fixed-broadband subscriptions [ITU]
1960	:	0.0	:	:	:	:
1961	:	:	:	:	:	:
1962	:	:	:	:	:	:
1963	:	:	:	:	:	:
1964	:	:	:	:	:	:
1965	:	0.0	:	:	:	:
1966	:	:	:	:	:	:
1967	:	:	:	:	:	:
1968	:	:	:	:	:	:
1969	:	:	:	:	:	:
1970	:	0.0	:	:	:	:
1971	:	:	:	:	:	:
1972	:	:	:	:	:	:
1973	:	:	:	:	:	:
1974	:	:	:	:	:	:
1975	:	0.0	:	:	:	:
1976	:	0.0	:	:	:	:
1977	:	0.0	:	:	:	:
1978	:	0.0	:	:	:	:
1979	:	0.0	:	:	:	:
1980	:	0.0	:	:	:	:
1981	:	0.0	:	:	:	:
1982	:	0.0	:	:	:	:
1983	:	0.0	:	:	:	:
1984	:	0.0	:	:	:	:
1985	:	0.0	:	:	:	:
1986	:	0.0	:	:	:	:
1987	:	0.1	:	:	:	:
1988	:	0.1	:	:	:	:
1989	:	0.1	:	:	:	:
1990	:	0.2	:	:	:	:
1991	:	0.3	:	:	:	:
1992	:	0.4	:	:	:	:
1993	:	0.6	:	:	:	:
1994	:	1.0	:	:	:	:
1995	:	1.6	:	:	:	:
1996	:	2.5	:	:	:	:
1997	4.0	3.7	2.0	14.0	:	:
1998	5.0	5.3	3.0	14.0	:	:
1999	8.0	8.1	5.0	15.0	:	:
2000	12.0	12.1	7.0	16.0	:	:
2001	15.5	15.5	8.0	16.6	:	0.6
2002	18.4	18.6	10.7	17.2	:	1.0
2003	22.2	22.3	12.3	17.8	:	1.6
2004	27.3	27.4	14.1	18.7	:	2.4
2005	33.9	33.9	15.8	19.1	:	3.4
2006	41.7	41.8	17.6	19.2	:	4.3
2007	50.6	50.5	20.6	18.8	4.0	5.2
2008	59.7	59.7	23.1	18.5	6.3	6.1
2009	68.0	67.9	25.6	18.4	9.0	6.9
2010	76.6	76.5	29.2	17.8	11.5	7.6
2011	83.8	84.2	31.7	17.2	16.7	8.4
2012	88.1	88.5	34.8	16.7	21.7	9.0
2013	93.1	93.1	37.2	15.9	27.3	9.9
2014	96.8	96.8	40.5	15.1	36.7	10.1
2015	98.6	98.6	43.8	14.3	44.2	11.2
2016	99.7	:	47.1	13.7	49.4	11.9

Table E6: Global market share for telecommunication technologies
(Sources: [International Telecommunication Union, The World Bank, 2016, UK Data Service, 2017])

Delivery Year	Number of aircraft deliveries by market class																			Market share of Jet A/C delivered (based on total number of A/C, not engine quantities, and including turboprops) [%]
	Business Jets	Business Turboprops	Civil Piston Helicopters	Civil Turbine Helicopters	Combat - Frontline	Combat - Support	Military Piston Helicopters	Military Turbine Helicopters	Narrowbody Jets	Regional Jets	Regional Turboprops	Tiltrotor - Military	Trainers	Utility Jets	Utility Pistons	Utility Turboprops	Widebody Jets	All classes	Total number of Jet A/C delivered (including turboprops)	
1949	:	:	:	:	:	:	3	:	1	:	:	:	:	:	:	:	:	4	**1**	25.00
1950	:	:	:	:	:	:	5	:	1	:	1	:	:	:	:	:	:	7	**2**	28.57
1951	:	:	1	:	:	:	97	:	:	:	:	:	:	:	:	:	:	98	**0**	0.00
1952	:	:	10	:	:	:	220	:	11	:	:	:	:	:	:	:	:	241	**11**	4.56
1953	:	:	18	:	:	:	273	:	9	:	22	:	:	:	:	:	:	322	**31**	9.63
1954	:	:	36	:	:	:	241	:	1	:	22	:	:	:	:	:	:	300	**23**	7.67
1955	:	:	25	:	:	2	296	:	:	:	44	:	:	:	:	:	:	367	**46**	12.53
1956	:	:	42	39	:	10	405	:	16	:	83	:	:	:	:	:	:	595	**148**	24.87
1957	:	:	29	78	:	177	474	:	30	:	113	:	:	:	:	:	:	901	**398**	44.17
1958	:	:	5	71	:	220	423	4	41	:	198	:	:	:	:	12	:	974	**546**	56.06
1959	:	:	1	75	:	210	238	41	189	:	364	:	:	:	:	72	:	1190	**951**	79.92
1960	:	:	2	246	:	148	188	208	304	:	196	:	:	:	:	76	:	1368	**1178**	86.11
1961	:	:	10	198	:	141	297	260	220	:	233	:	:	:	:	54	:	1413	**1106**	78.27
1962	:	:	115	220	:	240	92	567	200	:	189	:	:	:	:	101	:	1724	**1517**	87.99
1963	:	:	171	228	:	254	96	718	128	:	177	:	:	:	:	118	:	1890	**1623**	85.87
1964	:	:	172	201	:	257	61	724	220	:	175	:	:	:	:	122	:	1932	**1699**	87.94
1965	8	:	210	191	3	170	12	1203	311	:	188	:	:	:	:	163	:	2459	**2237**	90.97
1966	10	:	296	160	1	183	15	1734	418	2	260	:	:	:	:	136	:	3215	**2904**	90.33
1967	6	1	152	450	2	214	10	2641	541	2	386	:	:	:	5	120	:	4530	**4363**	96.31
1968	7	1	351	599	9	131	3	3079	764	9	491	:	:	:	10	101	:	5555	**5191**	93.45
1969	5	4	155	1100	7	149	:	2766	594	56	411	:	:	:	26	89	4	5366	**5185**	96.63
1970	2	1	135	907	13	133	:	2062	267	71	273	:	:	:	22	122	92	4100	**3943**	96.17
1971	6	:	138	992	12	138	:	1790	210	78	215	:	:	:	27	108	84	3798	**3633**	95.66
1972	10	2	151	1085	6	104	:	1145	185	125	144	:	:	:	12	84	99	3152	**2989**	94.83
1973	7	3	228	1302	:	107	:	604	225	147	199	:	2	:	23	73	125	3045	**2792**	91.69
1974	15	3	271	1390	:	86	:	734	329	132	194	:	7	8	16	120	115	3420	**3126**	91.40
1975	16	16	268	1528	2	127	:	465	307	149	160	:	3	18	20	192	98	3369	**3078**	91.36
1976	11	18	266	1197	4	104	:	497	303	153	138	:	12	29	17	245	76	3070	**2775**	90.39
1977	7	16	316	1302	:	92	:	480	257	108	111	:	:	18	22	223	59	3011	**2673**	88.77
1978	11	23	252	1254	1	88	:	550	345	78	134	:	:	24	7	300	72	3139	**2880**	91.75
1979	17	32	174	1398	:	78	:	392	388	35	177	:	:	56	9	289	142	3187	**3004**	94.26
1980	16	20	237	1712	1	81	:	486	400	25	215	:	:	45	2	319	180	3739	**3500**	93.61
1981	6	15	285	1665	3	87	:	459	405	16	231	:	:	43	1	272	147	3635	**3349**	92.13
1982	15	10	168	1288	1	96	:	549	262	11	161	:	:	46	1	234	116	2958	**2789**	94.29
1983	4	12	89	981	1	83	:	577	221	26	139	:	:	54	3	236	132	2558	**2466**	96.40
1984	8	2	84	873	3	110	:	569	188	28	177	:	:	56	1	226	105	2430	**2345**	96.50
1985	2	5	133	777	:	115	:	655	255	31	211	:	:	56	2	261	101	2604	**2469**	94.82
1986	3	2	143	918	:	111	:	685	308	33	284	:	:	54	1	190	104	2836	**2692**	94.92
1987	2	6	166	718	:	120	:	620	335	25	297	:	:	73	5	234	102	2703	**2532**	93.67
1988	7	1	245	813	:	106	:	543	399	29	342	:	:	82	2	219	136	2924	**2677**	91.55
1989	10	2	391	861	:	93	:	563	426	63	354	:	:	68	:	213	136	3180	**2789**	87.70
1990	13	10	513	964	:	102	:	633	505	49	413	:	:	58	3	205	177	3645	**3129**	85.84
1991	11	9	466	926	:	111	:	435	606	74	374	:	:	57	:	121	207	3397	**2931**	86.28
1992	4	2	292	768	:	101	:	324	584	72	292	:	:	62	:	83	220	2804	**2512**	89.59
1993	11	11	208	644	:	49	:	558	392	99	233	:	:	42	:	65	216	2528	**2320**	91.77
	8	1	232	463	:	49	:	345	296	87	234	:	:	29	:	80	159	1983	**1751**	88.30
1995	17	:	222	441	:	59	:	451	235	102	276	:	:	18	:	118	160	2099	**1877**	89.42
1996	7	2	221	500	:	40	:	320	234	96	274	:	:	9	:	104	170	1977	**1756**	88.82
1997	17	3	256	538	:	17	:	300	356	114	208	:	:	10	:	76	206	2101	**1845**	87.82
1998	20	6	296	510	:	20	:	243	543	155	195	1	:	4	:	68	246	2307	**2010**	87.13
1999	42	2	323	530	2	35	:	149	638	216	132	3	:	2	:	75	255	2404	**2078**	86.44
2000	27	1	372	550	2	54	:	145	594	307	122	9	:	1	:	59	197	2440	**2059**	84.39
2001	30	:	417	596	:	43	:	250	633	346	96	:	:	3	:	50	202	2666	**2249**	84.36
2002	34	:	297	584	:	35	:	313	497	311	77	2	:	:	:	42	175	2367	**2068**	87.37
2003	25	2	453	548	2	45	:	205	424	322	38	6	:	1	:	31	154	2256	**1797**	79.65
2004	24	3	709	602	:	50	:	154	452	315	47	9	:	8	:	40	148	2561	**1843**	71.96
2005	40	2	752	675	:	40	:	171	512	250	46	22	:	3	:	29	151	2693	**1919**	71.26
2006	72	3	826	744	:	49	:	290	626	178	80	15	:	2	:	31	185	3101	**2260**	72.88
2007	81	2	922	962	:	63	:	293	685	192	109	13	:	2	:	39	196	3559	**2624**	73.73
2008	78	3	875	1050	:	66	:	284	666	231	124	18	:	2	:	46	175	3618	**2725**	75.32
2009	62	10	480	1057	:	65	:	466	761	190	126	21	:	4	:	58	204	3504	**3003**	85.70
2010	64	3	322	956	:	70	:	531	758	144	136	27	:	2	:	64	188	3265	**2916**	89.31
2011	50	2	273	963	:	86	:	629	773	160	137	32	:	6	:	63	215	3389	**3084**	91.00
2012	60	2	317	1026	:	71	:	675	854	134	132	41	:	2	:	76	308	3698	**3340**	90.32
2013	46	2	308	1235	:	75	:	695	919	143	136	27	:	1	:	95	338	4020	**3685**	91.67
2014	43	6	287	986	:	84	:	698	957	180	145	41	:	2	:	52	373	3854	**3526**	91.49
2015	33	7	280	913	:	85	:	553	966	172	138	16	:	2	:	44	404	3613	**3317**	91.81
2016	24	10	256	683	:	90	:	568	1025	171	123	19	:	3	:	23	400	3395	**3120**	91.90
2017	24	18	168	1056	:	103	:	818	1085	238	210	24	:	16	:	54	417	4231	**4039**	95.46
Grand Total	**1178**	**317**	**17284**	**48287**	**75**	**6322**	**3449**	**39866**	**27590**	**6480**	**12362**	**346**	**24**	**1081**	**237**	**7215**	**8671**	**180784**	**159444**	**88.20**

Table E7: Global market share for turbojets based on the number of aircraft deliveries by market class (Source: [Flight Global, 2017])

Appendix F - Model features, supporting logic, user-defined inputs, auxiliary variables, and equations

Table F1: Model features and supporting rationale

Model feature No.	Feature / relationship logic
1	Technological paradigms are framed within scientific paradigms [Constant, 1973]
2	Displacement, velocity and momentum analogies can be used to describe large technological systems [Hughes et al., 1987, David, 1991]. Individuals can gauge the likelihood of technological impacts from changes in relative accelerations Relative distance to fringes of scientific and technological fields is an indicator of alignment to existing paradigms [Constant, 1973]
3	Negative hype (disillusionment) following early technological and commercial failures, coupled with a greater understanding of technical limitations, deflates confidence in new technologies following initial surge in expectations
4	Advances observed in other fields of science and technology can increase agent uncertainty and self-doubt about current technological paradigms
5	Presumptive leaps are often made by individuals aware of the current rate of scientific advance in fields outside of their native field of expertise [Hughes et al., 1987, Constant, 1973, Rogers, 2010] Predisposition of early adopters to rely on external influences more than later adopters [Chatterjee and Eliashberg, 1990, Dattée and Weil, 2007, Rogers, 2010, National Academy of Engineering, 2013]

Continued on next page

Table F1 – continued from previous page

Model feature No.	Feature / relationship logic
6	Confidence in a new technology requires scientific and technological evidence, as well as overall market credibility As rates of scientific and technological advances vary the population's perception of obstacles to continued development in emerging technologies adjusts to match Confidence in a given technology increases as visibility of supporting scientific fields increases [Rogers et al., 2005, Dattée and Weil, 2007] Population's confirmation bias loop: population's tendency to reinforce evidence that supports new technology as confidence increases (looping from confidence to persuasiveness to credibility to confidence)
7	Until a competing framework exists, association with anomalies will be rejected by scientific and technological communities [Kuhn, 1996]
8	Industry resistance to moving away from 'normal' technology [Constant, 1973, Kuhn, 1996]
9	If reverse salients cannot be resolved with current paradigm, then these can support questioning of fundamental assumptions [Hughes et al., 1987]. This affects the population's perception of the rate of advances being made
10	Adopter categories based on classic technology adoption model [Rogers et al., 2005, Rogers, 2010]
11	Influence (from social interactions) and marketing (external influences) included as in Bass model [Bass, 1969, 2004] Critical mass of adopters needed for technological revolutions to take place, akin to 'Little's Wall' [Constant, 1973, Rogers et al., 2005] Once critical mass occurs, rate of adoption is no longer linear and innovation diffusion is no longer only local [Rogers et al., 2005]
12	1,000 agents sufficient to generate necessary adoption dynamics [Goldenberg et al., 2001]
13	Having a large power base (i.e. strong backing) accelerates the rate of adoption [Constant, 1973, Bass, 1969, 2004]
14	Agent's power is taken to be a combination of agent's control of resources and expertise (in this case represented by the agent's credibility). This is based on a simplified version of French and Raven's framework on the sources of power (1960) [French et al., 1959]

Continued on next page

Table F1 – continued from previous page

Model feature No.	Feature / relationship logic
15	Utility of technologies increases as uncertainty reduces, leading to reduced risk averseness (and vice versa) [Rogers et al., 2005, Chatterjee and Eliashberg, 1990, Dattée and Weil, 2007] Visibility of other scientific and technical fields is required to build some insight or to imitate (i.e. not persuasive if either of these are absent) [Rogers et al., 2005, Dattée and Weil, 2007] Productivity paradox time lag in technological gains can predict non-trivial substitution patterns (surprise, disappointment, hype, etc.) [David, 1991, Dattée and Weil, 2007, Ruttan et al., 2008]
16	Having a large influence (i.e. strong marketing presence) accelerates the rate of adoption [Constant, 1973, Bass, 1969, 2004]
17	Individuals require significant resources and investment to create a supporting framework for new technologies [Constant, 1973]
18	De-valuing of resources and skills if not in demand [Rogers et al., 2005, Dattée and Weil, 2007]
19	The degree of cultural similarity/difference (homophily/heterophily) has a large possible impact on perceived credibility [Rogers et al., 2005, Dattée and Weil, 2007, Deffuant et al., 2000] Inclusion of network externalities [Goldenberg et al., 2001, Peres et al., 2010]
20	Agents can earn credibility by conforming to existing norms, demonstrating consistent performance, behaving sociably, or being supported by strong backers [Rogers et al., 2005] Credibility of agent also represents the perceived expertise that this agent can provide
21	As credibility of agent/domain increases the likelihood that it will influence other entities increases [Constant, 1973, Rogers et al., 2005]
22	Agents use collected referrals to decide whether or not to heed paradigms proposed by a given agent [Rogers et al., 2005, Dattée and Weil, 2007, Yu and Singh, 2002] 'Systems builders' need to have sufficient experience across a broad range of domains in order to create new frameworks [Hughes et al., 1987]
23	Increasing confidence in a new technology encourages more individuals to recognise the potential of the same frameworks and technologies

Continued on next page

Table F1 – continued from previous page

Model feature No.	Feature / relationship logic
24	Critical mass of adopters needed for technological revolutions to take place, akin to 'Little's Wall' [Constant, 1973, Rogers et al., 2005] Once critical mass occurs, rate of adoption is no longer linear and innovation diffusion is no longer only local [Rogers et al., 2005]
25	Lack of interest to buy current products indicates a switch to new technologies [Ruttan et al., 2008]
26	Decreasing sales leads to poorer finances
27	Decision-making logic: for an individual to decide to adopt a new product the expectation of performance has to exceed the sum of foreseen risks and price hurdles [Chatterjee and Eliashberg, 1990]

In conjunction with these features Table **F2**, Table **F3**, and Table **F4** below provide a description of the user-defined variables, primary assumptions behind derived auxiliary variables, and equations used in the model. One point worth noting regarding the user-defined inputs and auxiliary variables considered is the use of normalisation when dealing with conventionally intangible metrics such as *confidence*, *persuasiveness*, or *credibility*, etc. This ensures that a simplified numerical approach is adopted throughout for these difficult to quantify terms, but if implementing this framework as an agent-based model it would be possible to extend this representation to probability distributions and fuzzy sets in order to improve the realism of the behavioural model [Vos, 2015, Kirkwood, 2005].

Table F2: Simulation variables: user-defined inputs

VARIABLE	UNITS	VALUE RANGE	DESCRIPTION
Anomaly normalisation constant	Dimensionless	Any positive value greater than 0	Constant for use in anomaly accumulation normalisation functions based on the format: f(x) = x / (x + a). This means that the normalised value goes from 0 to 1 as x goes from 0 to infinity
Maximum number of agents supported (market carrying capacity)	No. of agents	0 to user-defined upper limit	Used to indicate the population size at which resource scarcity effects will begin to be observed (competition for resources increase as the population nears/exceeds this limit). Relationship between population size and market carrying capacity is defined using the logistic function provided in Table F3
Maximum number of events observed per time step	Events/Year	0 to user-defined upper limit	The maximum possible number of anomaly-related events that the Poisson distribution could predict to occur for any given time step (i.e. upper bound). This is typically set to a value much larger than the mean to avoid constraining the result. Setting a low value implies that the realised mean will be less than the mean parameter, due to truncation of the distribution
Maximum time to resolve an event	Years	0 to user-defined upper limit	The maximum time for anomaly-related events to be resolved and/or reclassified as new inventions or discoveries
Mean number of events observed per time step	Events/Year	0 to user-defined upper limit	The mean value of the Poisson distribution used to predict the occurrence of anomaly-related events
Minimum number of events observed per time step	Events/Year	0 to user-defined upper limit	The minimum possible number of anomaly-related events that the Poisson distribution could predict to occur for any given time step (i.e. lower bound)
Minimum time to resolve an event	Years	0 to user-defined upper limit	The minimum time for anomaly-related events to be resolved and/or reclassified as new inventions or discoveries

Table F2 – continued from previous page

VARIABLE	UNITS	VALUE RANGE	DESCRIPTION
New technology normalisation constant	Dimensionless	Any positive value greater than 0	Constant for use in technology classification model component normalisation functions based on the format: f(x) = x / (x + a). This means that the normalised value goes from 0 to 1 as x goes from 0 to infinity
Poisson distribution shift	Events/Year	Any positive or negative value	Translation in time of the Poisson distribution. Ordinarily this is set to 0
Poisson distribution stretch	Dimensionless	Any positive or negative integer values	Scaling of the Poisson distribution. Ordinarily this is set to 1. Non-integer values will result in draws that may not be integers
Random number seed	Dimensionless	Positive integer values	Random number seed. 0 uses default noise seed
Rate of adoption gain	$Years^{-1}$	0 to user-defined upper limit	Used as a control to regulate how fast adoption occurs in relation to the current population adopter fraction and the coefficients of internal and external influence used in the Bass diffusion model
Rate of presumption gain	$Years^{-1}$	0 to user-defined upper limit	Used as a control to regulate how fast presumption occurs in the population in relation to the current presumption fraction and global levels of confidence in both new and existing technologies
Total number of agents	No. of agents	0 to user-defined upper limit	Defines the overall population size

Table F3: Simulation variables: assumed conditions for calculated auxiliary variables

AUXILIARY VARIABLE *(y)*	UNITS	CAUSAL INFLUENCES	CONDITIONS	DERIVED CAUSAL RELATIONSHIP
Credibility of new technology	Dimensionless (normalised)	A. Number of new technology adopters B. Total number of agents C. Persuasiveness of new technology D. Financial situation of new technology advocates	1) $A = 0, y = 0$ 2) $C \,\&\, D = 0, y = 0$ 3) $C + D \leq 1$	$y = \frac{A}{B}\left(\frac{C+D}{2}\right)$
Disillusionment with new technology	Patent counts	A. Running maximum of technological development efforts for the new technology B. Technological development efforts for the new technology	1) $A \geq B$ 2) $y \geq 0$	$y = A - B$
Financial situation of new technology advocates	Dimensionless (normalised)	A. Financial situation of existing technology advocates	1) $A = 1, y = 0$ 2) $A = 0, y = 1$	$y = 1 - A$
Global level of confidence in existing technology	Dimensionless (normalised)	A. Scientific development efforts for the new technology B. Technological development efforts, taking into account disillusionment, for the new technology C. Lack of interest to buy existing technology D. Number of anomaly-related events not yet resolved	1) $A, B, C \,\&\, D = 0, y = 1$ 2) $A + B + C + D \leq 1$	$y = 1 - \left(\frac{A+B+C+D}{4}\right)$
Global level of confidence in new technology	Dimensionless (normalised)	A. Scientific development efforts for the new technology B. Technological development efforts, taking into account disillusionment, for the new technology C. Credibility of the new technology	1) $A, B \,\&\, C = 0, y = 0$ 2) $A + B + C \leq 1$	$y = \frac{A+B+C}{3}$
Global level of resources available to agents	Dimensionless (normalised)	A. Total number of agents B. Maximum number of agents supported (market carrying capacity)	1) $\frac{A}{B} = 0, y = 1$ 2) $\frac{A}{B} > 1, y \to 0$	$y = d + \frac{(a-d)}{\left[1+\left(\frac{A/B}{c}\right)^{b}\right]^{e}}$ $\left(\begin{array}{c} 5PL\ asymmetrical\ sigmoidal \\ logistic\ function \end{array}\right)$ $a = 0.95$ $b = 5.64$ $c = 8.68$ $d = -0.0095$ $e = 658016$
Lack of interest to buy existing technology	Dimensionless (normalised)	A. Number of agents that presume technological substitution required B. Total number of agents	1) $A = 0, y = 0$ 2) $A = B, y = 1$	$y = \frac{A}{B}$
New technology's sphere of influence	Dimensionless (normalised)	A. Credibility of the new technology B. Resources available to new technology advocates	1) $A \,\&\, B = 0, y = 0$ 2) $A + B \leq 1$	$y = \frac{A+B}{2}$

Table F3 – continued from previous page

AUXILIARY VARIABLE (*y*)	UNITS	CAUSAL INFLUENCES	CONDITIONS	DERIVED CAUSAL RELATIONSHIP
Number of anomaly-related events not yet resolved	Events	A. Number of anomaly-related events observed for the existing technology B. Number of anomaly-related events resolved for the existing technology	1) $A \geq B$ 2) $y \geq 0$	$y = A - B$
Persuasiveness of new technology	Dimensionless (normalised)	A. Scientific development efforts for the new technology (normalised) B. Technological development efforts, taking into account disillusionment, for the new technology (normalised) C. Global confidence in new technology D. Resources available to new technology advocates	1) $A\ OR\ B = 0, y = 0$ 2) $A\ \&\ B \neq 0, y = f(C, D)$ 3) $C\ OR\ D = 0, y = 0$	$\begin{cases} AB = 0, y = 0 \\ AB \neq 0, y = CD \end{cases}$
Power of new technology advocates	Dimensionless (normalised)	A. Credibility of the new technology B. Resources available to new technology advocates	1) $A\ OR\ B = 0, y = 0$	$y = AB$
Rate of adoption of new technology	Agents/Year	A. Rate of adoption gain B. Total number of agents C. Number of new technology adopters D. Persuasiveness of new technology E. Power of new technology advocates F. New technology's sphere of influence G. Global confidence in existing technology	1) $A = 0, y = 0$ 2) $B = C, y = 0$ 3) $E + F \leq 1$	$y = A(B - C)\left(D\left(\frac{E+F}{2}\right) + C\left(\frac{1-G}{B}\right)\right)$
Rate of presumption	Agents/Year	A. Rate of presumption gain B. Total number of agents C. Number of agents that presume technological substitution required D. Global confidence in new technology E. Global confidence in existing technology	1) $A = 0, y = 0$ 2) $B = C, y = 0$ 3) $D + E \leq 1$	$y = A(B - C)\left(\frac{C}{B}\right)\left(\frac{D+E}{2}\right)$
Rate of resolution of anomaly-related events	Events/Year	A. Number of anomaly-related events not yet resolved B. Time taken to resolve an anomaly-related event	1) $A = 0, y = 0$ 2) $y \geq 0$	$y = \max\left(\frac{A}{B}, 0\right)$
Resources available to new technology advocates	Dimensionless (normalised)	A. Global level of resources available to agents B. Financial situation of new technology advocates	1) $A\ OR\ B = 0, y = 0$	$y = AB$
Time taken to resolve an anomaly-related event	Years	A. Maximum time to resolve an event B. Minimum time to resolve an event C. Technological development efforts for the new technology (normalised)	1) $A \geq y \geq B$ 2) $C = 1, y = B$	$y = \max(A(1 - C), B)$

The causal relationships shown in Table **F3** do not provide the literal equations used in the system dynamics model, but instead express algebraic forms of the relationships derived for these equations that link the key causal influences based on the conditions shown. The actual Vensim version of these equations can be found in Table **F4**.

Table F4: Full details of equations used in the technology substitution model

Equation No.	Equation
1	Anomaly normalisation constant = 257.5 **Units:** Events [0,200,1]
2	Area under disillusionment curve[Technology] = INTEG (ABS(Disillusionment with new technology[Technology]),0) **Units:** Year Displacement measure to show how far new technology has been set back by disillusionment (i.e. the hype cycle)
3	Area under science component curve[Technology] = INTEG (ABS(Science component of classification model[Technology]),0) **Units:** Year
4	Area under technology component curve minus disillusionment area[Technology] = IF THEN ELSE(Area under technology component curve[Technology] - Area under disillusionment curve[Technology] > 0 , Area under technology component curve[Technology] - Area under disillusionment curve[Technology] , 0) **Units:** Year
5	Area under technology component curve[Technology] = INTEG (ABS(Technology component of classification model[Technology]),0) **Units:** Year
6	New technology normalisation constant = 1 **Units:** Dmnl [0,5,0.01]
7	Credibility of agents supporting new technology[Technology] = (((Number of agents adopting new technology[Technology]/Total number of agents)^(1/1)) * 1/1) * (((Persuasiveness of agents supporting new technology[Technology]^(1/1)) * 1/2) + ((Financial situation of agents supporting new technology[Technology]^(1/1)) * 1/2)) **Units:** Dmnl
8	Delayed maximum of technology component[Technology] = DELAY FIXED ("Real-time maximum of technology component"[Technology], TIME STEP , 0) **Units:** Dmnl
9	Disillusionment with new technology[Technology] = IF THEN ELSE(Technology component of classification model[Technology] = 0 , 0 , "Real-time maximum of technology component"[Technology] - Technology component of classification model[Technology]) **Units:** Dmnl

Table F4 – continued from previous page

Equation No.	Equation
10	FINAL TIME = 180 **Units:** Year The final time for the simulation
11	Financial situation of agents supporting existing technology[Technology] = 1-"Lack of interest to buy existing technology (market delay)"[Technology] **Units:** Dmnl
12	Financial situation of agents supporting new technology[Technology] = 1 - Financial situation of agents supporting existing technology[Technology] **Units:** Dmnl
13	Global confidence in existing technology[Technology] = MIN(1 - ((Normalised area under science component curve[Technology])^(1/1) * 1/4) - ((Normalised area under technology component curve minus disillusionment area[Technology])^(1/1) * 1/4) - ((Lack of interest to buy existing technology[Technology])^(1/1) * 1/4) - ((Normalised number of anomaly-related events not yet resolved[Technology])^(1/1) * 1/4) , 1) **Units:** Dmnl
14	Global confidence in new technology[Technology] = ((Credibility of agents supporting new technology[Technology])^(1/1) * 1/3) + ((Normalised area under science component curve[Technology])^(1/1) * 1/3) + ((Normalised area under technology component curve minus disillusionment area[Technology])^(1/1) * 1/3) **Units:** Dmnl
15	Global level of resources available to agents[Technology] = MAX((-0.0095 + ((0.95 + 0.0095) / ((1 + (((Total number of agents/"Maximum number of agents supported (market carrying capacity)") / 8.68)^5.64))^658016))),1e-006) **Units:** Dmnl [0,1] Current equation: logistic function based on curve-fit (see http://mycurvefit.com/ - type 5PL)
16	INITIAL TIME = 0 **Units:** Year The initial time for the simulation
17	Lack of interest to buy existing technology[Technology] = (Number of agents that presume technological substitution required[Technology])/Total number of agents **Units:** Dmnl [0,1]

Table F4 – continued from previous page

Equation No.	Equation
18	"Lack of interest to buy existing technology (market delay)"[Technology] = DELAY FIXED (Lack of interest to buy existing technology[Technology], 0.25, 0) **Units:** Dmnl [0,1]
19	"Maximum number of agents supported (market carrying capacity)" = 1500 **Units:** Agents [0,10000,100]
20	Maximum number of anomaly-related events observed per time step = 1e+006 **Units:** Events/Year Maximum possible number of events; set to a value much larger than mean to avoid constraining the result. Setting a low value implies that the realised mean will be less than the mean parameter, due to truncation of the distribution
21	Maximum time to resolve an anomaly-related event = 1 **Units:** Year [0,50,0.2]
22	Mean number of anomaly-related events observed per time step = 0.5 **Units:** Events/Year [0,20,0.1] Poisson mean (lambda parameter). Equals mean of result as long as the minimum and maximum number of anomaly-related events observed per time step do not truncate the distribution
23	Minimum number of anomaly-related events observed per time step = 0 **Units:** Events/Year Minimum possible number of events
24	Minimum time to resolve an anomaly-related event = 0.1 **Units:** Year [0,1,0.01]
25	Normalised area under science component curve[Technology] = Area under science component curve[Technology] / (Area under science component curve[Technology] + Components normalisation constant) **Units:** Dmnl Normalisation function based on the format: f(x) = x / (x + a). For notes on this see: https://math.stackexchange.com/questions/869150/a-function-fx-that-increases-from-0-to-1-when-x-increases-from-0-to-infinity

Table F4 – continued from previous page

Equation No.	Equation
26	Normalised area under technology component curve minus disillusionment area[Technology] = ABS(Area under technology component curve minus disillusionment area[Technology]) / (ABS(Area under technology component curve minus disillusionment area[Technology]) + Components normalisation constant) **Units:** Dmnl Normalisation function based on the format: f(x) = x / (x + a). For notes on this see: https://math.stackexchange.com/questions/869150/a-function-fx-that-increases-from-0-to-1-when-x-increases-from-0-to-infinity
27	"Normalised area under technology component curve (normalised relative to anomalies)"[Technology] = Area under technology component curve[Technology] / (Area under technology component curve[Technology] + (1 / Anomaly normalisation constant)) **Units:** Dmnl Normalisation function based on the format: f(x) = x / (x + a). For notes on this see: https://math.stackexchange.com/questions/869150/a-function-fx-that-increases-from-0-to-1-when-x-increases-from-0-to-infinity
28	Normalised number of anomaly-related events not yet resolved[Technology] = ACTIVE INITIAL (Number of anomaly-related events not yet resolved[Technology] / (Number of anomaly-related events not yet resolved[Technology] + Anomaly normalisation constant),0) **Units:** Dmnl Normalisation function based on the format: f(x) = x / (x + a). For notes on this see: https://math.stackexchange.com/questions/869150/a-function-fx-that-increases-from-0-to-1-when-x-increases-from-0-to-infinity
29	Number of agents adopting new technology[Technology]= INTEG (Rate of adoption of new technology[Technology],1) **Units:** Agents
30	Number of agents that presume technological substitution required[Technology] = INTEG (Rate of presumption of agents[Technology],1) **Units:** Agents [0,?]
31	Number of anomaly-related events not yet resolved[Technology] = Number of anomaly-related events observed in the current field of technology[Technology] - Number of anomaly-related events resolved in the current field of technology[Technology] **Units:** Events
32	Number of anomaly-related events observed in the current field of technology per time step[Technology] = RANDOM POISSON(Minimum number of anomaly-related events observed per time step, Maximum number of anomaly-related events observed per time step , Mean number of anomaly-related events observed per time step , Poisson distribution shift , Poisson distribution stretch , Random number seed) **Units:** Events/Year

Table F4 – continued from previous page

Equation No.	Equation
33	Number of anomaly-related events observed in the current field of technology[Technology] = INTEG (Number of anomaly-related events observed in the current field of technology per time step[Technology],1e-008) **Units:** Events
34	Number of anomaly-related events resolved in the current field of technology[Technology]= INTEG (Rate of resolution of anomaly-related events[Technology],1) **Units:** Events
35	Percent of agents that presume technological substitution required[Technology] = Lack of interest to buy existing technology[Technology] * 100 **Units:** Dmnl [0,100]
36	Persuasiveness of agents supporting new technology[Technology] = DELAY FIXED (IF THEN ELSE((Normalised area under science component curve[Technology] * Normalised area under technology component curve minus disillusionment area[Technology]) = 0 , 0 , ((Resources available to agents supporting new technology[Technology])^(1/1) * (Global confidence in new technology[Technology])^(1/1) * 1)), 0.5, 0) **Units:** Dmnl [0,1]
37	Poisson distribution shift = 0 **Units:** Events/Year Shift in the Poisson distribution. Ordinarily set to 0
38	Poisson distribution stretch = 1 **Units:** Dmnl Scaling of the distribution; ordinarily set to 1. Non-integral values will result in draws that may not be integers
39	Power of agents supporting new technology[Technology] = ((Credibility of agents supporting new technology[Technology]^(1/1)) * 1/1) * ((Resources available to agents supporting new technology[Technology]^(1/1)) * 1/1) **Units:** Dmnl [0,1]
40	Random number seed = 1 **Units:** Dmnl [1,10000,1] Random number seed. 0 uses default noise seed
41	Rate of adoption gain = 0.5 **Units:** 1/Year [0,1,0.01]

Table F4 – continued from previous page

Equation No.	Equation
42	Rate of adoption of new technology[Technology] = (Total number of agents-Number of agents adopting new technology[Technology])*Rate of adoption gain*(((Persuasiveness of agents supporting new technology[Technology]^(1/1))*((Power of agents supporting new technology[Technology]^(1/1) * 1/2)+("Size of new technology's sphere of influence (across different community groups)"[Technology]^(1/1) * 1/2)) * 1) + (((1 - Global confidence in existing technology[Technology])/Total number of agents)*Number of agents adopting new technology[Technology])) **Units:** Agents/Year The rate of adoption of an agent's current paradigm is adapted from the Bass Diffusion model: dN(t)/dt = [m - N(t)][p + (q/m)N(t)] This version of Bass model taken from (Niu, 2002), where p is the coefficient of innovation, and q is the coefficient of imitation (as labelled in (Makinen, Kanniainen & Dedehayir, 2013)). These terms are also defined in (Peres, Muller & Mahajan, 2010) as: external influences (p), such as advertising and other communications initiated by the firm, and internal market influences (q) that result from interactions among adopters and potential adopters in the social system. The Bass model states that the probability that an individual will adopt the innovation - given that the individual has not yet adopted it - is linear with respect to the number of previous adopters. Here p = ((Persuasiveness of disruptive agents^(1/1))*((Power of disruptive agents^(1/1) * 1/2)+("Size of disruptive agents' sphere of influence (across different community groups)"^(1/1) * 1/2)) * 1) and q = 1 - Global confidence in central paradigm
43	Rate of presumption gain = 1 **Units:** 1/Year [0,10,0.05]
44	Rate of presumption of agents[Technology] = Rate of presumption gain * (Total number of agents - Number of agents that presume technological substitution required[Technology]) * ((Global confidence in new technology[Technology]^(1/1) * 1/2) + ((1 - Global confidence in existing technology[Technology])^(1/1) * 1/2)) * (Number of agents that presume technological substitution required[Technology]/Total number of agents) **Units:** Agents/Year The rate of presumption of the need for a technological revolution is adapted from the Bass Diffusion model: dN(t)/dt = [m - N(t)][p + (q/m)N(t)] This version of Bass model taken from (Niu, 2002), where p is the coefficient of innovation, and q is the coefficient of imitation (as labelled in (Makinen, Kanniainen & Dedehayir, 2013)). These terms are also defined in (Peres, Muller & Mahajan, 2010) as: external influences (p), such as advertising and other communications initiated by the firm, and internal market influences (q) that result from interactions among adopters and potential adopters in the social system. The Bass model states that the probability that an individual will adopt the innovation - given that the individual has not yet adopted it - is linear with respect to the number of previous adopters. Here p = 0 and q = ((Global confidence in new disruptive paradigm^(1/1) * 1/2) + ((1 - Global confidence in central paradigm)^(1/1) * 1/2))

Table F4 – continued from previous page

Equation No.	Equation
45	Rate of resolution of anomaly-related events[Technology] = ACTIVE INITIAL (MAX((1/Time taken to resolve an anomaly-related event[Technology]) * Number of anomaly-related events not yet resolved[Technology] , 0),0) **Units:** Events/Year
46	"Real-time maximum of technology component"[Technology] = ACTIVE INITIAL (IF THEN ELSE(Technology component of classification model[Technology] > Delayed maximum of technology component[Technology], Technology component of classification model[Technology] , Delayed maximum of technology component[Technology]),0) **Units:** Dmnl
47	Resources available to agents supporting new technology[Technology] = Global level of resources available to agents[Technology] * Financial situation of agents supporting new technology[Technology] **Units:** Dmnl [0,1]
48	SAVEPER = TIME STEP **Units:** Year [0,?] The frequency with which output is stored
49	Science component of classification model[Technology] = "Science component of classification model (lookup data for all technologies)"[Technology]((Time / 1) + 0) **Units:** Dmnl [?,?,0.05]
50	"Size of new technology's sphere of influence (across different community groups)"[Technology] = ((Credibility of agents supporting new technology[Technology]^(1/1)) * 1/2) + ((Resources available to agents supporting new technology[Technology]^(1/1)) * 1/2) **Units:** Dmnl [0,1]
51	Technology component of classification model[Technology] = "Technology component of classification model (lookup data for all technologies)"[Technology]((Time / 1) + 0) **Units:** Dmnl
52	TIME STEP = 0.0833333 **Units:** Year [0,?] The time step for the simulation
53	Time taken to resolve an anomaly-related event[Technology] = MAX((1 - "Normalised area under technology component curve (normalised relative to anomalies)"[Technology]) * Maximum time to resolve an anomaly-related event , Minimum time to resolve an anomaly-related event) **Units:** Year [0,200,0.25]
54	Total number of agents = 1000 **Units:** Agents [0,1e+006,100]